Université de Montréal

# A Time-use Compositional Analysis of The Association Between Movement Behaviours and Depressive Symptoms in Young Adults

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*Ce mémoire intitulé*

**A time-use compositional analysis of the association between movement behaviours and depressive symptoms in young adults**

*Présenté par*
**Fady Michael**

*A été évalué(e) par un jury composé des personnes suivantes*

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# Résumé

**Contexte**: La dépression chez les jeunes est un problème de la santé publique croissant. L'activité physique (AP), les comportements sédentaires (CS) et le sommeil représentent des facteurs de risque modifiables des symptômes dépressifs. La compréhension de comment le temps passé quotidiennement dans l'ensemble de l'AP, des CS et du sommeil est associée aux symptômes dépressifs peut éclairer les interventions qui aident à prévenir les symptômes dépressifs chez les jeunes adultes.

**Objectifs**: Ce mémoire vise à estimer l'association entre la proportion de temps sur une période de 24 heures alloué à l'AP d'intensité modérée à vigoureuse (APMV), la marche, les CS et le sommeil, et les symptômes dépressifs chez les jeunes adultes. Il vise à estimer le changement des symptômes dépressifs avec la réaffectation du temps entre les comportements.

**Méthodes**: Les données de l'étude Nicotine Dependence in Teens (NDIT), une étude longitudinale en cours qui a recruté 1294 élèves de 7e année dans 10 écoles secondaires à Montréal, au Canada, ont été utilisées. Les données pour ce projet ont été collectées à 20 et 24 ans à l'aide de questionnaires auto-rapportés. Une analyse compositionnelle a été effectuée. La taille de l'effet de l'association a été estimée par un modèle de réaffectation du temps.

**Résultats**: Aucune association statistiquement significative a été observée entre les proportions de temps passé en APMV ($p = 0,273$), la marche ($p = 0,861$), le CS ($p = 0,723$) et le sommeil ($p = 0,948$) et les symptômes dépressifs chez les jeunes adultes. La réaffectation de 15 minutes d'APMV aux CS est associée à une augmentation de 3% des symptômes dépressifs. La réaffectation de 15 minutes de CS à l'APMV est associée à une réduction de 1% des symptômes dépressifs. Cependant, ces changements étaient également non significatifs.

**Conclusion**: Le temps alloué à l'APMV, la marche, les CS et le sommeil n'étaient pas associés aux symptômes dépressifs chez les jeunes adultes. La réaffectation du temps entre les comportements de mouvement a entraîné des changements non significatifs des symptômes dépressifs. Ces résultats devront être vérifier avant de formuler des recommandations.

**Mots-clés** : Activité Physique, Comportements Sédentaires, Sommeil, Jeunes adultes, Symptômes Dépressifs

# Abstract

**Background**: Depression among youth is a growing public health burden. Physical activity (PA), sedentary behaviours (SB) and sleep are modifiable risk factors for depressive symptoms. Understanding how the interplay between the mix of time spent in daily in all of PA, SB and sleep is associated with depressive symptoms may inform interventions that help prevent depressive symptoms in young adults

**Objectives**: This thesis aims to estimate the association between the proportion of time spent during a 24-hour period in each of moderate-to-vigorous intensity PA (MVPA), walking, SB and sleep, and depressive symptoms in young adults. It also aims to estimate change in depressive symptoms with the reallocation of time across movement behaviours.

**Methods**: Data were drawn from the Nicotine Dependence in Teens (NDIT) study, an ongoing longitudinal study that recruited 1294 7$^{th}$ grade students in 10 secondary schools in Montreal, Canada. Data were collected using self-report questionnaires at ages 20 and 24. PA, SB and sleep were analyzed using time-use compositional analysis. Effect size of the association was estimated using a compositional time reallocation model.

**Results**: There was no statistically significant association between the proportion of time spent in MVPA (p=0.273),walking (p=0.861), SB (p=0.723) or sleep (p=0.948) and depressive symptoms in young adults. There was 3% increase in depressive symptoms with reallocation of 15 minutes from MVPA to SB and 1% reduction in depressive symptoms with reallocation of 15 minutes from SB to MVPA. However, these changes were similarly non-significant

**Conclusion**: Time-use in MVPA, walking, SB and sleep overall was not associated with depressive symptoms in young adults in our study. Reallocating time between movement behaviours resulted in minimal non-significant changes in depressive symptoms. Replication is needed before our findings can be translated to recommendations.

**Keywords**: Physical Activity, Sedentary Behaviours, Sleep, Youth, Depressive Symptoms, Compositional Analysis

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# List of Acronyms and Abbreviations

CANMAT: Canadian Network for Mood and Anxiety Treatments

CEGEP: Collège d'Enseignement Général Et Professionnel

CoDA: Compositional Data Analysis

BMI: Body Mass Index

DAG: Directed Acyclic Graph

DSM-5: Diagnostic and Statistical Manual of Mental Disorders-5

EMA: Ecological momentary assessment

Ilr: Isometric Log-ratio

IPAQ-SF: International Physical Activity Questionnaire Short Form

MAOI: Monoamine Oxidase Inhibitors

MDD: Major Depressive Disorder

MDI: Major Depression Inventory

MET: Metabolic Equivalent

MPA: Moderate Physical Activity

MVPA: Moderate to Vigorous Physical Activity

NDIT: Nicotine Dependence in Teens

PA: Physical Activity

SB: Sedentary Behaviours

SSRI: Selective Serotonin Reuptake Inhibitors

TCA: Tricyclic Antidepressants

VPA: Vigorous Physical Activity

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# Chapter 1: Introduction

Major depression disorder, usually referred to as Depression, is a mood disorder characterized by intense feelings of sadness for a period of time long enough to interfere with the capacity to function (Beers & Merck Research, 2006). Depression can present with many symptoms including low mood, markedly diminished interest, psychomotor retardation, loss of appetite, lack of sleep, energy and concentration and a sensation of guilt that sometimes results in suicidal ideation (American Psychiatric Association, 2013). While depression as a disorder differs from depressive symptoms, many epidemiological studies choose to examine depressive symptoms as they are easily measurable using self-reports and they are strong predictors of depression (Pine, Cohen, Cohen, & Brook, 1999). The prevalence of depression and depressive symptoms has been increasing over the last decade (World Health Organization, 2017). Globally, more than 300 million individuals worldwide suffer from depression, representing 4.4% of the population worldwide. About 17 million people in the U.S. are affected, representing 5.9% of the U.S. population (World Health Organization, 2017). In Canada, 1.5 million or 4.7% of the Canadian population have depression (Statistics Canada, 2013). Among all Canadians, youth between ages 15–24 years have the highest rate of mood disorder and in 2012, 7% reported having depression in the last 12 months (Statistics Canada, 2013).

Early adulthood is a critical period for mental health development and the onset of mental illness including depression (Naicker, Galambos, Zeng, Senthilselvan, & Colman, 2013; Patel, Flisher, Hetrick, & McGorry, 2007). It is also a period of sometimes challenging transitions. Multiple life-defining events take place during this period such as changing relationship status, enrolling in or graduating from college and exploring career choices (Arnett, 2000). The interaction between these life events and emotional and mental development during young adulthood may contribute to increased depressive symptoms (Friis, Wittchen, Pfister, & Lieb, 2002). Depressive symptoms among young adults cause cognitive impairment, threaten academic achievement and can decrease work performance, all of which can impact an individual's career path and social life negatively, and in some cases lead to suicide ideation and suicide, which is the second leading cause of death among Canadian youth ages 15–24 (Glied

& Pine, 2002; Statistics Canada, 2018). Since young adulthood is the period during which depressive symptoms peak, it is crucial to examine modifiable risk factors for depressive symptoms during this life period (Ferro, Gorter, & Boyle, 2015; Patel et al., 2007).

Many potential risk factors for depression have been identified including behaviours such as physical activity (PA), sedentary behavior (SB) and sleep, psychosocial factors including coping strategies (Garnefski, Legerstee, Kraaij, van Den Kommer, & Teerds, 2002), genetic polymorphisms (Cadoret, O'Gorman, Heywood, & Troughton, 1985) and environmental factors (Cadoret et al., 1985; Saveanu & Nemeroff, 2012). Movement behaviours including PA, SB and sleep and their associations with depressive symptoms have been of great interest to public health research. Higher levels of PA are generally associated with fewer depressive symptoms; longer duration of higher PA intensity (i.e., moderate to vigorous PA (MVPA)) is associated with better depression outcomes (Bailey, Hetrick, Rosenbaum, Purcell, & Parker, 2018). Higher SB levels are generally associated with poorer mental health outcomes including depression (Suchert, Hanewinkel, & Isensee, 2015). Finally, sleep duration between 6-8 hours daily is associated with better emotional regulation and fewer depressive symptoms compared to sleep durations less than 6 hours daily (Chaput et al., 2016).

Extant literature in this field usually examines the simple association between each of PA, SB and sleep with depressive symptoms. Recently, the focus has shifted to the importance of examining the mix of time spent in PA, SB and sleep together in association with a variety of health outcomes. Tremblay et al. suggested that since they all fit on the movement continuum, balancing daily time in PA, SB and sleep is needed to achieve optimal health (Tremblay, Esliger, Tremblay, & Colley, 2007). Zhai et al., suggested that an increase in SB time may come at the expense of PA time and by decreasing PA time, SB may increase the risk of depressive symptoms (Zhai, Zhang, & Zhang, 2015). Similarly, Chaput et al. suggested that long sleep duration may come at the expense of time spent in PA which can negatively influence different health outcomes (Chaput et al., 2016). The recent introduction of the Canadian 24-hour movement behaviours guidelines for adults ages 18–64 (Ross et al., 2020) highlights the

importance of balancing daily time between PA, SB and sleep to achieve optimal health and avoid mental illness.

PA, SB and sleep are modifiable risk factors for depression that can be targeted by public health interventions. Examining whether and how strongly PA, SB and sleep together are associated with depressive symptoms could contribute to better conceptualization of public health programs that aim to influence these behaviours in ways that can help prevent and treat depression. The aim of this thesis is to examine the interplay between time spent daily in PA, SB, and sleep and how this interplay is associated with depressive symptoms during young adulthood. Data for this project were drawn from the Nicotine Dependence in Teens (NDIT) study. Chapter 2 of the thesis includes a review of the existing literature on the epidemiology of depression and the mechanisms underpinning the association between movement behaviours including PA, SB and sleep and depressive symptoms. Chapter 3 identifies the objectives and hypotheses of this project. The study sample, variables, analytic procedure and ethical consideration are discussed in Chapter 4. Results of the project are reported in manuscript format in Chapter 5. Discussion of the results, their interpretation and future directions are detailed in Chapter 6. Finally, Chapter 7 includes conclusions of this thesis.

# Chapter 2: Literature Review

## 2.1 Descriptive Epidemiology of Depression

Mental illness is a major public health concern. Worldwide, it is one of the leading causes of disease and disability (James et al., 2018). Mental illness comprises psychiatric conditions that affect thoughts and feelings and limit the ability to function in social, work and family activities (American Psychiatric Association, 2013). They include among others, psychotic, mood, anxiety, eating, personality, sleep, neurocognitive, neurodevelopmental and substance-related disorders (American Psychiatric Association, 2013). The most common mental illness by far is depression - about 322 million people worldwide have depression (World Health Organization, 2017).

Depressive symptoms is a term representing a range of depression-related symptoms such as low mood, loss of interest, psychomotor retardation, loss of appetite, lack of sleep, energy and concentration and a sensation of guilt (American Psychiatric Association, 2013). Major depressive episode is a medical diagnosis that is usually established by a clinician when a person presents a specific number of depressive symptoms for at least 2 weeks' duration (American Psychiatric Association, 2013). Presence of multiple major depressive episodes that last for at least 2 weeks is a discrete characteristic of a Major depressive disorder, which is usually referred to as depression (American Psychiatric Association, 2013).

In Canada, in 2012, the 12-month prevalence of major depression was 4.7% in the general population age 15 years or older (Statistics Canada, 2013). Although this prevalence rate has remained stable for the past 15 years, it is slightly higher than the comparable rate across the world (4.4%) (World Health Organization, 2017). Females have a higher 12-month prevalence of depression (5.8%) than males (3.6%) (Statistics Canada, 2013) in all age groups except among persons age 65 or older, in whom the prevalence is similar in males and females (Pearson, Janz, & Ali, 2013). About 3.5 million Canadians (12.6%) meet the criteria for a mood disorder during their lifetime. Major depression disorder accounts for most cases of mood

disorders; about 3.2 million people in Canada (11.3%) had symptoms consistent with depression (Pearson et al., 2013). By 2041, it is estimated that 8.9 million Canadians will be living with a mental illness, representing a 31% increase compared to a 26% projected population growth (Mental Health Commission of Canada, 2013). In Quebec, depression prevalence is highest across sex and all age groups in Canada (Statistics Canada, 2013). In 2012, persons in Quebec age 15 or older had a 12% lifetime risk of developing a major depressive episode (Baraldi, Bordeleau, Plante, & Joubert, 2015). Moreover, females in Quebec are more likely to develop a major depressive episode (15%) compared to males (9.3%) (Baraldi et al., 2015). In addition, Quebec reported the highest average number of comorbid diagnoses due to psychiatric reasons per hospitalization (Sambell, Quan, & Johansen, 2006)

Canadian adolescents and young adults have the highest prevalence of mental illness across all age groups (Statistics Canada, 2013). By 2041, it is estimated that 1.2 million Canadian youth between ages 9 and 19 years will be living with a mental illness (Smetanin, Briante, Stiff, Ahmad, & Khan, 2015). The most prevalent mental disorder in Canadian youth is depression; 10.7% of youth between ages 15 and 24 years develop a major depressive episode during their lifetime (Mental Health Commission of Canada, 2013). Young women are twice as likely as young men to report depression (12% vs. 5%) (Mental Health Commission of Canada, 2013). Young people who experience mental illness are at a higher risk of mental illness than adults; more than 50% who have an episode of major depression experience a recurrence (Mental Health Commission of Canada, 2013). Among university students, depressive symptoms were associated with lower academic performance and university students with depression report higher rates of failing exams, dropping courses and missing social activities (Hysenbegasi, Hass, Rowland, & economics, 2005). Moreover, mental illness is increasingly threatening the lives of Canadian youth. Canada's youth suicide rate is the third highest in the industrialized world. Suicide is among the leading causes of death in 15–24 year-old Canadians, second only to accidents; and 4,000 people die prematurely each year by suicide (Mental Health Commission of Canada, 2013). In Quebec, in 2012, the lifetime risk of having a major depressive episode among persons ages 15 to 24 was 12.7% which was higher than the Canadian average (10.7%) (Baraldi et al., 2015; Statistics Canada, 2013). In addition, the proportion of

persons ages 15 to 24 in Quebec who reported having an episode of depression in the last 12 months was the highest across all age groups (8.2%). 3.7 % of youth ages 15 to 24 in Quebec reported having tried to commit suicide at least once in their life (Baraldi et al., 2015).

The economic cost of mental illness in Canada was estimated at $7.9 billion in 1993 (Moore, Mao, Zhang, & Clarke, 1997) and increased to $14.4 billion by 1998 (Lim, Jacobs, Ohinmaa, Schopflocher, & Dewa, 2008). In 2011, the total economic burden was estimated at $51 billion per year, representing 2.8% of Canada's gross domestic product. Over the next 30 years, the total projected cost to the economy is estimated at $2.5 trillion (Mental Health Commission of Canada, 2013).

## 2.2 Depression Diagnosis, Treatment and Prevention

### 2.2.1 Depression Diagnosis

Sadness and grief are normal emotional reactions to life stress and loss. However, depression differs from "normal" in presentation, with generally higher ranges in intensity of low mood and loss of interest in activities usually enjoyed (American Psychiatric Association, 2013). In addition, depression can present with one or more of psychomotor retardation, loss of appetite, lack of sleep, energy and concentration and a sensation of guilt that sometimes results in suicidal ideation (American Psychiatric Association, 2013). These symptoms can last for time periods long enough to cause disruption in life and inability to cope with pressure (American Psychiatric Association, 2013).

Depression is usually diagnosed by a qualified health professional such as a general practitioner or psychiatrist, after a complete clinical assessment of mood, thought processes and overall mental state. This assessment is based on the diagnostic criteria of Diagnosis and Statistical Manual (DSM-5) (American Psychiatric Association, 2013) for major depressive disorder, which necessitates the presence of five or more of the following symptoms: depressed

mood, diminished interest in activities, unintentional change in weight associated with changes in appetite, irritability, fatigue, lack of ability to concentrate and feelings of worthlessness and guilt with or without thoughts of death or suicidal ideation for a period of at least two weeks (American Psychiatric Association, 2013). However, a depression diagnosis is affected by the generally limited access to health services, especially in rural areas in Canada (Friesen, 2019). Only 29–52% of those with major depression seek medical help within the first year of being affected (Wang et al., 2007). In addition to limited access to medical services, fear of exposure to the stigma of psychiatric illness among those with mental disorders prevents people from seeking professional help (Sartorius, 2007). In 2012, of 4.9 million Canadians (17%) who perceived a need for mental health care, only 67% had their needs met; 21% reported that their needs were partially met; and 12% never received the care they needed (Statistics Canada, 2013).

### 2.2.2 Depression Treatment

Once diagnosed, depression can be treated with pharmacotherapy, psychotherapy, electro-convulsive therapy or a combination of these treatments, based on patient preference and clinician assessment. Depression can be treated using multiple pharmacological medications including tricyclic antidepressants (TCA), monoamine oxidase inhibitors (MAOI) and selective serotonin reuptake inhibitors (SSRI). Although these medications are effective in treating depression, there is a high rate of nonadherence to antidepressant therapy due to their side effects, fear of addiction and patient uncertainty of treatment efficacy (Sansone & Sansone, 2012). About 50% of psychiatric patients discontinue their antidepressant therapy prematurely (Sansone & Sansone, 2012). Psychotherapy (i.e., a type of talk therapy) aims to modify feelings, thoughts, cognitions and behaviours of individuals with a mental illness. Efficacy of psychotherapy is similar to antidepressant medication for treating mild and moderate depression and even more effective for treating stress-related mental disorders (Hunsley, Elliott, & Therrien, 2013; Smith, 2007). In addition to the traditional methods of treating depression, PA has been recommended in the most recent version of the Canadian Network for Mood and Anxiety Treatments (CANMAT) guidelines as a first- or second-line treatment for mild to

moderate depression (Bailey et al., 2018; Carter, Morres, Meade, & Callaghan, 2016; Ravindran et al., 2016).

Electro-convulsive therapy is a procedure performed under anaesthesia that aims to change brain chemicals by inducing convulsions using well-measured electrical stimulation (Payne & Prudic, 2009). Although effective and safe, electro-convulsive therapy is only used in cases of severe refractory depression or when there are contraindications to other methods of treatment, since it is considered to be the most stigmatizing method of treatment in psychiatry (Payne & Prudic, 2009).

The United States Preventive Services Task Force recommends screening for major depressive disorder beginning at age 12 (US Preventive Services Task Force, 2009). In contrast, the Canadian Task Force on Preventive Health Care recommends against routinely screening for depression due to the lack of evidence about the benefits or potential harms of false-positive diagnoses with unnecessary treatment (Joffres et al., 2013).

### 2.2.3 Depression Prevention

Although depression can be effectively treated, few people, especially youth, seek treatment because of limited access to psychiatric health services, cost and fear of the stigma of mental illness (Peachey & Hicks, 2013). The multiple challenges in terms of treating depression, its increasing prevalence and the economic burden associated with depression have resulted in an increased focus on preventing depression.

A major challenge in preventing depression however, is lack of clarity in regard to time of onset (Jaycox, Reivich, Gillham, & Seligman, 1994), which relates to the non-specific nature of its symptoms (Backenstrass et al., 2006), and the need for a clinician diagnosis (American Psychiatric Association, 2013). This lack of clarity blurs the distinction between primary and

secondary prevention (Albee & Gullotta, 1986; Jaycox et al., 1994). Thus, the focus of research in depression prevention has shifted from diagnosis to identification of symptoms that indicate a risk for developing depression onset or the onset of a depression disorder (Jaycox et al., 1994; Lewinsohn, Hoberman, & Rosenbaum, 1988).

Early adulthood is a critical period for mental health development and mental illness onset (Naicker et al., 2013; Patel et al., 2007). Although depression is often detected later in life, it usually arises between ages 12 and 24 years (Patel et al., 2007). Evidence suggests that the risk of developing depression relates, among others, to genetic and biological factors (Kendler et al., 2010; Silberg et al., 1999). However, multiple environmental, economic and social factors during adolescence and early adulthood can interact with biological factors to modify the risk of developing depression (Eley et al., 2004; Patel et al., 2007). Modifiable risk factors for depression such as movement behaviours including PA, SB and sleep during adolescence and early adulthood, can reduce depressive symptoms and prevent depression onset and its peak during this period in the life course (Lopresti, Hood, & Drummond, 2013). It is crucial to examine these risk factors for depression during this period and to target them with effective preventive intervention before depressive symptoms interfere with academic achievement, career development and young people ability to contribute meaningfully to their communities (Ferro et al., 2015; Patel et al., 2007).

## 2.3 PA, Sedentary Behaviour and Sleep as Movement Behaviours

The effect of movement behaviours including PA, SB and sleep on health indicators has been of public health interest for more than 100 years. Studies on the association between PA and health date back to the 19$^{th}$ century when vigorous intensity PA was thought to be harmful to health (MacAuley, 1994; Morgan, 1873), to the eventual discovery that PA in fact, increased average life expectancy (Morgan, 1873). In addition, the study of sleep epidemiology was first introduced in 1979 (Bixler, Kales, Soldatos, Kales, & Healey, 1979; Pedišić, Dumuid, & S Olds, 2017). However, it was not until 2000, when the concept of sedentary behaviours was viewed

as distinct from physical inactivity, and included low energy activities such as sitting, watching television, and automobile transport (Owen, Leslie, Salmon, & Fotheringham, 2000). In 2007, Tremblay et al. suggested that balancing daily time between PA, SB and sleep, since they all fit on the movement continuum (Figure 1), is needed to achieve optimal health (Tremblay et al., 2007).

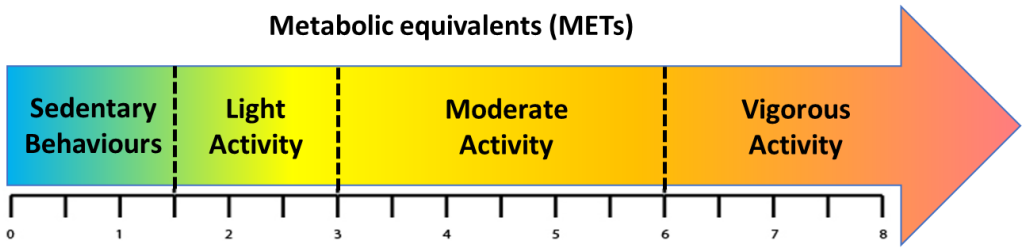


Figure 1. The Movement Behaviour Continuum

### 2.3.1 PA

PA, defined as any bodily effort using skeletal muscles that requires energy expenditure of more than 1.5 MET, is an important predictor of depression (Poitras et al., 2016). However, despite widespread the recognition that PA has major benefits for physical and mental health, most Canadians do not attain PA recommendations. In 2011, using accelerometers to measure PA, the Canadian Health Measures Survey found that only 15% of Canadian adults met the recommended 150 minutes of MVPA weekly (Rachel C Colley et al., 2011a, 2011b). Men are more physically active than women and time spent being physically active generally declines with age (Rachel C Colley et al., 2011a, 2011b). In regard to walking, only 35% of Canadian adults accumulate the recommended target of 10,000 steps daily (Rachel C Colley et al., 2011a, 2011b).

### 2.3.2 Sedentary Behaviours

SB are defined as any bodily activity that requires an energy expenditure of 1.5 METS or less (i.e., using a computer, watching television, other screen time activities) (Mansoubi et al., 2015). Sedentary behaviours account for the majority of waking hours (50–60%) among Canadian youth (R. C. Colley et al., 2011) . In 2011, Statistics Canada reported that Canadian youth are sedentary 8 hours per day, and Canadian adults are sedentary for over 9.5 hours daily (Rachel C Colley et al., 2011a, 2011b). In addition, relative to the current Canadian movement behaviour guidelines that recommend no more than 2 hours of sedentary behaviours daily among children and adolescents (Tremblay et al., 2016), three-quarters of pre-school children in Canada have too much screen time daily (Garriguet et al., 2016). Youth ages 12 to 17 have higher average daily screen time compared to children ages 5 to 11 (3.8 versus 2.3 hours). Boys average 3.3 hours screen time daily compared to 2.8 in girls (Roberts et al., 2017). Among adults ages 50 or less, the time spent in passive travel and screen time for leisure has been increasing (Prince et al., 2020).

### 2.3.3 Sleep

Sleep is defined as the biological state in which the body and mind relax to renew energy, enhance the ability to cope with life, and maintain good mental and physical health (Barbara & Philips, 2006). In Canada, only 68% of children ages 10 to 13 years and 72% of adolescents ages 14 to 17 years meet the current Canadian recommendations of 8–10 hours of sleep daily. In 2017, Patte et al., reported that sleep duration in Canadian adolescents declined over three study waves between 2013-2016 (Patte, Qian, & Leatherdale, 2017), and recommended continued surveillance of the extent of sleep deprivation among Canadian youth (Patte et al., 2017). In 2002, the Canadian community health survey showed that 35% of Canadian ages 15 and older had difficulty going to sleep. Between 2007 and 2013, 31% of Canadians ages 18 to 64 reported sleeping less than 7 hours daily (Statistics Canada, 2014).

### 2.3.4 Movement Behaviours

Movement behaviours, a term that represents the collectivity of PA, SB and sleep, predict health indicators including mental state and depression (Carson, Chaput, Janssen, & Tremblay, 2017). Although sleep and SB are distinct from PA, all three behaviours are on the same movement continuum (Tremblay, Colley, Saunders, Healy, & Owen, 2010) and together comprise the 24-hour period of the day (Tremblay et al., 2016). Time allocated to each of PA, SB and sleep sum up to the total of 24-hour period, which means that a change in one behaviour is necessarily associated with a change in one or both of the other behaviours (Dumuid, Stanford, Pedišić, et al., 2018). Analytically, all three factors can be examined concurrently using a method that takes their multicollinear nature into consideration (Pedišić et al., 2017). In addition to their multicollinearity within the 24-hour period, numerous studies suggest that PA, SB and sleep influence each other. For example, among 14,782 students in grades 9–12, those with a daily PA duration ≥60 minutes had a higher odds of sufficient sleep compared to students with less PA (Foti, Eaton, Lowry, & McKnight-Ely, 2011). Students who watched TV ≥4 hours/day had a higher odds of sufficient sleep, while those who played video or computer games ≥ 2 hours/day had a lower odds of sufficient sleep (Foti et al., 2011).

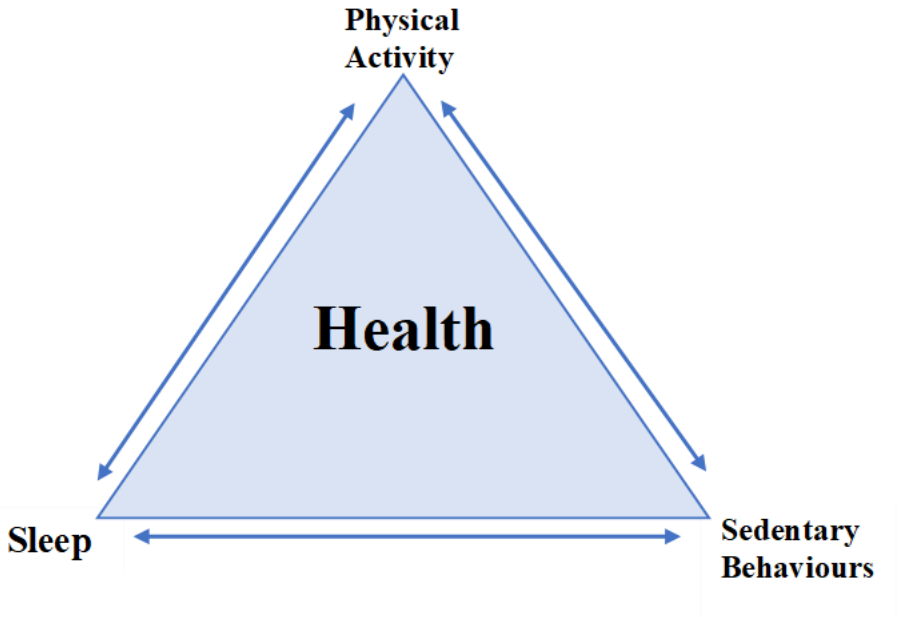


Figure 2. Compositional Nature of Movement Behaviours and Its Association with Health

The Canadian 24-hour movement guidelines for children and youth ages 5–17 years (i.e., the world's first movement behaviour guidelines) highlight the importance of considering PA, SB and sleep throughout the day when investigating the benefits of each on health among children and youth ages 5–17 years (Tremblay et al., 2016). These guidelines recommend that youth should have at least 60 minutes per day of MVPA, 8 to 10 hours of sleep per night, and no more than 2 hours of recreational screen time daily to prevent disease and promote health (Tremblay et al., 2016). The health benefits of adherence to these recommendations were examined in 4,157 Canadian children and youth ages 5 to 17. Relative to meeting all three recommendations, meeting none or meeting one or two recommendations was associated with higher BMI and higher waist circumference (Carson et al., 2017). Meeting or not meeting specific combinations of these recommendations in isolation was less important for health, compared to the number of recommendations met (Carson et al., 2017). The 24-hour movement behaviour guidelines for adults ages 18 to 64 years was recently released (Ross et al., 2020), which recommend accumulating 150 minutes of MVPA per week, obtaining 7 to 9 hours of sleep daily with consistent wake and sleep hours, and limiting SB to a maximum of 8 hours per day (Ross et al., 2020). These guidelines do not apply to women who are pregnant or adults living with a disability or certain medical conditions. However, confirmation of the benefits of attaining these recommendations on physical and mental health remains elusive.

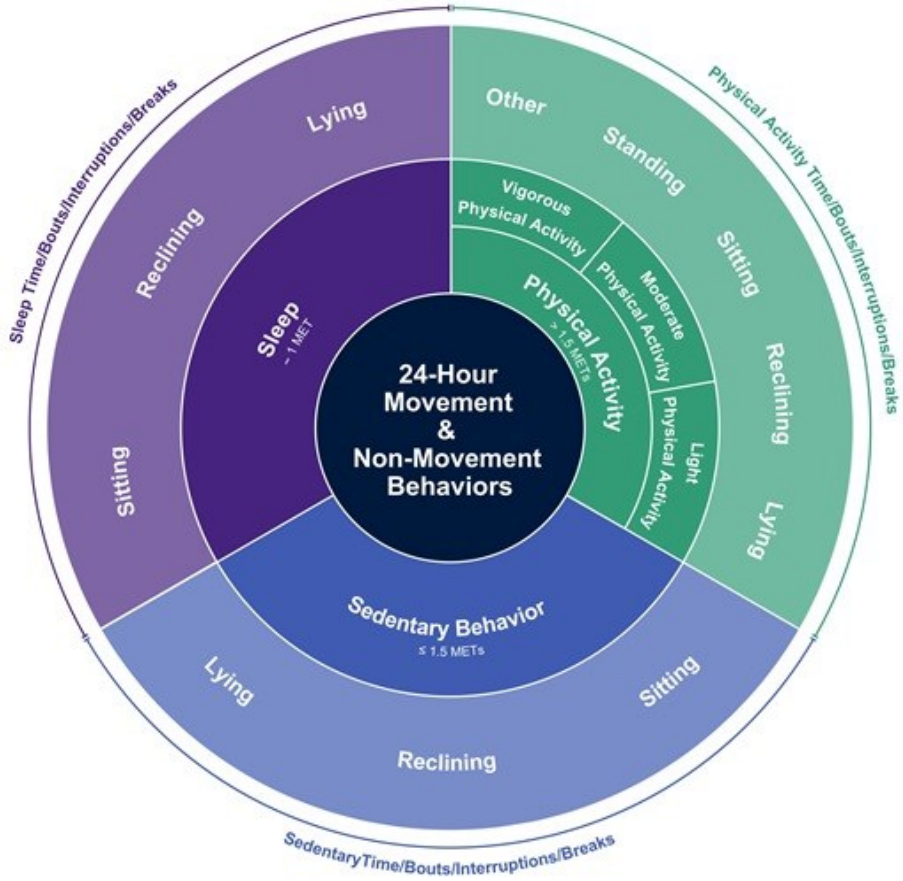


Figure 3. Conceptual Framework Underpinning The 24-hour Movement Behaviour Guidelines (Tremblay et al., 2017).

## 2.4 Movement Behaviours and Depression

Positive change in any movement behaviours including PA, SB and sleep may help reduce depressive symptoms while avoiding the negative side effects of the medications usually used to treat depression (Bailey et al., 2018; Carter et al., 2016).

### 2.4.1 PA and Depression

Multiple randomized controlled trials report that the effect of exercise on mild and moderate depression is equivalent to that of antidepressant medication (Blumenthal et al., 2007; Brenes et al., 2007; Hoffman et al., 2011). Higher PA levels are associated with better cognitive

function in young adults (Poitras et al., 2016). PA interventions targeting depression in youth appear to have a role in depression prevention and treatment (Brown, Pearson, Braithwaite, Brown, & Biddle, 2013) and PA has been recommended by the Canadian Network for Mood and Anxiety Treatments (CANMAT) as a first- or second-line treatment for mild to moderate depression (Bailey et al., 2018; Carter et al., 2016; Ravindran et al., 2016). Moreover, there appears to be a dose-response association such that longer duration and more intense PA (i.e., MVPA) are associated with better depression outcomes compared to light intensity PA (Bailey et al., 2018). Further, the context in which PA is undertaken may have an independent effect on mood. PA in the context of team sport is associated with better mental health and fewer depressive symptoms compared to sports outside a team context (Doré, O'Loughlin, Schnitzer, Datta, & Fournier, 2018) .

Overall, PA is associated with lower levels of depressive symptoms and PA interventions targeting young adults with depression appear to be effective in decreasing depressive symptoms (Biddle, Ciaccioni, Thomas, & Vergeer, 2018). However, whether the association between PA and depression is causal in young adults is unknown since longitudinal studies fall short by exploring PA in healthy young adults for relatively short durations (Biddle et al., 2018).

### 2.4.2 SB and Depression

Lower SB levels are associated with favourable mental health outcomes, while levels exceeding the recommended "no more than 2 hours of recreational screen time per day" are associated with lower self-esteem and poorer academic performance among youth (Carson et al., 2017). Similarly, high screen time levels have unfavourable effects on mental health among adolescents (Costigan, Barnett, Plotnikoff, & Lubans, 2013). While SB are associated with poorer mental health (Suchert et al., 2015), using the Internet and playing video games had a u-shaped association with depressive symptoms (Suchert et al., 2015) (i.e., adolescents using the Internet and video games in moderate amounts had the lowest prevalence of depressive symptoms). Nevertheless, whether the association is causal is not known (Suchert et al., 2015), since time spent in SB may reduce time spent in PA. Consistent evidence suggests that SB is a

risk factor for depression whereas PA is protective (Ahn & Fedewa, 2011; Biddle & Asare, 2011). Consequently, research is needed to explore the effect of movement behaviours collectively, to elucidate their joint association with depressive symptoms (Zhai et al., 2015).

### 2.4.3 Sleep and Depression

In youth, meeting the daily sleep recommendation of 8-10 hours per day (Tremblay et al., 2016) is essential for mental health, while shorter or longer sleep duration is associated with adverse mental health outcomes (Chaput et al., 2016) including the risk of major depression (Roberts & Duong, 2014). Adequate sleep duration, between 8–10 hours per night, is associated with better emotional regulation and better mental health outcomes such as depression and depressive symptoms (Chaput et al., 2016). Sleep disturbances in adolescents such as delayed sleep onset increase wakefulness in bed, which in return increases the risk of developing depressive symptoms such as irritability, fatigue and diminished ability to think or concentrate (Lovato & Gradisar, 2014). Sleep education improves mood and decreases irritability among youth (Tamura & Tanaka, 2014). Sleep deprivation (i.e., ≤ 6 hours of sleep) is associated not only with depressive symptoms (Roberts & Duong, 2014), but also with suicidal ideation among youth. A negative linear dose-response association has been identified between sleep with suicidal ideation, and there is an 11% decrease in the risk of suicide ideation with each additional hour of sleep (Chiu, Lee, Chen, Lai, & Tu, 2018). However, prolonged sleep duration is also associated with an increased risk of suicide, which may relate to the moderating effect of depressive symptoms (Chiu et al., 2018). Even though the importance of sleep for mental health and mood is well established, few studies examine the association between sleep and depression in youth while taking other movement behaviours into account (Chaput et al., 2016).

### 2.4.4 Combined Effect of PA, SB and Sleep in the Association Between Movement Behaviors and Depression

Several studies report that high SB levels can co-exist with high PA levels, so that both SB and PA should be included as independent variables in exploring their association with

mental health indicators (Hamer, Stamatakis, & Mishra, 2009; Kleppang, Thurston, Hartz, & Hagquist, 2017). Kremer & al (Kremer et al., 2014) reported that encouraging youth to do more PA and reduce screen time benefits mental health, although the effect on mental health could be explained by replacing sedentary time by PA (Ahn & Fedewa, 2011; Zhai et al., 2015). In a study of 1,486 adolescents, the combined effect of elevated TV-time and low PA increased psychological distress (Hamer et al., 2009). Further, including both PA and SB in the same model showed that SB is associated with moderate but not severe depressive symptoms among adolescents (Bélair, Kohen, Kingsbury, & Colman, 2018). A possible explanation is that PA negates the effect of SB among those with severe depressive symptoms (Bélair et al., 2018). High screen time and insufficient vigorous PA interact to increase psychological problems (Cao et al., 2011).

Both sleep and PA have independent associations with mental health in youth (Biddle et al., 2018; Chaput et al., 2016). Sleep and PA are associated, with PA being an important measure to improve sleep quality (Banno et al., 2018) and quantity (Youngstedt & Kline, 2006). Few studies to date however examine the combined effect of PA and sleep on depressive symptoms. In a cross-sectional study, Ogawa et al. reported that there is a positive impact of the interaction between adequate sleep and adequate PA on depression among 720 Japanese students between ages 12 and 17 years (Ogawa et al., 2018). However, the study was cross-sectional, thus lacking the temporality that enhances for causal inference.

In 2020, four studies examined the association between the mix of time spent in PA, SB and sleep daily and depressive symptoms. Larisch et al. used compositional data analysis to examine the association between accelerometer-measured movement behaviours and depressive symptoms among 349 office workers in Sweden (Larisch et al., 2020). Similarly, Curtis et al. and Fairclough et al. examined the same association among 430 Australian adults age 18-65 and 359 youth age 9-13 in England, respectively (Curtis et al., 2020; Fairclough et al., 2020). All three studies found no significant association between the proportion of time spent in PA, SB and sleep and depressive symptoms. However, del Prozo Cruz et al. who examined the

association between movement behaviours and depressive symptoms in 3233 adults age 18 or older in the US found that only the proportion of time spent in SB daily relative to other behaviours was significantly associated with depressive symptoms (del Pozo Cruz et al., 2020). While all four studies used accelerometer-measured movement behaviours in their investigation, the study designs were cross-sectional, and no study examined the association specifically in young adults (i.e., the age group in which depressive symptoms peak).

### 2.4.5 Mechanisms of Association

Multiple mechanisms contribute to the association between PA and depression. Biologically, PA activates short-term release of brain neurotransmitters such as serotonin, which play an important role in reducing depression (Wipfli, Landers, Nagoshi, Ringenbach, & sports, 2011). PA improves blood circulation with better regulation of the hypothalamic-pituitary-adrenal axis which in turn, helps control cortisol levels leading to an overall better physiological response to stress (Kandola et al., 2019). Evidence suggests that chronic low-grade inflammation contributes to depression (Gleeson et al., 2011). PA helps lower multiple blood circulating inflammatory factors, thereby reducing depression through its anti-inflammatory effect (Fedewa, Hathaway, & Ward-Ritacco, 2017). Psychologically, PA boosts self-esteem which mediates the lowering effect of PA on depressive symptoms among adolescents (McPhie, Rawana, & Activity, 2012). Socially, PA in a context of team sport is associated with lower depressive symptoms, which could relate to social interaction and connectedness among team members (Eime et al., 2013; Miller & Hoffman, 2009; Sabiston et al., 2016)

The mechanisms underpinning the association between SB and depressive symptoms are not well understood. SB cause social withdrawal and decrease levels of social interactions, thus increasing the risk of developing depressive symptoms (Zhai et al., 2015). In addition, increases in sedentary time may come at the expense of PA, which is known to regulate brain chemicals which maintain positive mental health. By decreasing PA time, SB may increase the risk of depressive symptoms (Zhai et al., 2015).

The exact pathophysiological mechanism that explains the association between sleep and depressive symptoms is unclear (Fang, Tu, Sheng, & Shao, 2019). However, lack of sleep contributes to activation of the sympathetic nervous system which in turn, activates inflammatory gene expression leading to elevation of cellular inflammation. The markers for cellular inflammation were high among depressed patients compared to non-depressed individuals, which might explain the association between sleep and depression (Fang, Tu, Sheng, & Shao, 2019).

## 2.5 Summary

Many studies explore whether PA, sleep or SB are independently associated with depression in young adults. The few studies that examine two movement behaviours concurrently in association with depressive symptoms do not account for possible multicollinearity across behaviours. Additionally, most studies are cross-sectional, and the data therefore lack the temporality that is necessary to enhance causal inference. To our knowledge, only four studies have examined the association between time-use in PA, SB and sleep and depressive symptoms using compositional data analysis (Curtis et al., 2020; del Pozo Cruz et al., 2020; Fairclough et al., 2020; Larisch et al., 2020). However, all four studies were cross-sectional, and none used compositional analysis to investigate this association in a longitudinal study design. This thesis aims to address these gaps by examining the association between the mix of time spent in PA, SB and sleep as component parts of the total 24-hour period, and depressive symptoms in young adults, in a longitudinal study design.

# Chapter 3: Objectives and Hypotheses

This M.Sc. thesis aims to examine the association between the mix of time spent in PA, SB and sleep as component parts of the total 24-hour period, and depressive symptoms in young adults. There are two specific objectives:

1. To estimate the association between the proportion of time spent during a 24-hour period in each of MVPA, walking, SB and sleep, and depressive symptoms in young adults.

   We hypothesize that the proportions of time spent daily in MVPA, walking, SB and sleep are significantly associated with depressive symptoms in young adults.

2. To estimate change in depressive symptoms with reallocation of time spent across pairs of different movement behaviours in young adults.

   We hypothesize that reallocating time from walking, SB or sleep to MVPA is associated with a reduction in depressive symptoms. Additionally, we hypothesize that reallocating time from MVPA to walking, SB or sleep is associated with an increase in depressive symptoms.

# Chapter 4: Methods

This thesis comprises a secondary analysis of data drawn from the Nicotine Dependence in Teens (NDIT) study. This chapter describes the study design, the sample, and the study variables. It also describes the analysis plan as well as ethical considerations.

## 4.1 NDIT Study Design and Sample

This project uses data drawn from the NDIT study, a 20-year longitudinal investigation of 1294 grade 7 students recruited in 1999–2000 in 10 high schools in Montreal, Canada (O'Loughlin et al., 2015). Its primary aim was to examine the natural course and determinants of cigarette smoking and nicotine dependence in adolescents (O'Loughlin et al., 2015). The scope of NDIT data collected is very broad, thereby permitting examination of a wide range of research questions pertaining to youth health (O'Loughlin et al., 2015). Briefly, data on PA, team sports, SB, diet, alcohol use, substance use, exposure to second-hand smoke, gambling, sleep, and mental and physical health were collected in self-report questionnaires completed by participants, their parents and school principals (O'Loughlin et al., 2015). Anthropometric indicators including height, weight and waist circumference and blood pressure were measured, and blood and saliva samples were obtained for genetic analyses. Finally, trained technicians collected context-relevant data on the school environment and in the school neighbourhood (O'Loughlin et al., 2015).

The source population for the NDIT sample was high school students in the greater Montreal area at study inception in 1999–2000. A school-based sampling strategy was used to recruit grade 7 students in 10 Montreal-area high schools purposively selected to include a mix of French- and English-language schools, urban, suburban and rural schools, and schools located in high, moderate and low socioeconomic status neighbourhoods (O'Loughlin et al., 2015). This purposive sampling was to enhance the probability that the sociodemographic characteristics of participants reflected those of the source population. Of the 13 schools approached that agreed to participate, two schools were excluded due to the low return of parental consent forms and

one school was excluded because its administrators could not guarantee continued participation in NDIT over five years. Thus, 10 schools were retained in the sample of schools. All 7th grade students in the 10 schools (n = 2,325) were invited to participate and 1,294 (56%) agreed to participate and provided informed consent (O'Loughlin et al., 2015).

At inception in 1999–2000, participants completed self-report questionnaires at school during class time. Follow-up questionnaires were completed every 3 months thereafter during the 10-month school year, for the following 5 years (1999–2005) until participants completed grade 11 and graduated from high school, for a total of 20 cycles (O'Loughlin et al., 2015). In cycle 21, self-report questionnaires were mailed to participants (then age 20 years on average) at home or questionnaires were completed online. In cycle 22 in 2011–12, NDIT participants (i.e., then age 24 years on average) completed self-report questionnaires administered in the NDIT research offices at CRCHUM (O'Loughlin et al., 2015). NDIT data collection for cycle 23 (age 31 years on average) was conducted in 2017–20 (completed in Feb 2020) and cycle 24 is currently ongoing (i.e., as of Nov 2020). This thesis uses data collected in cycles 21 and 22 (Fig. 4).

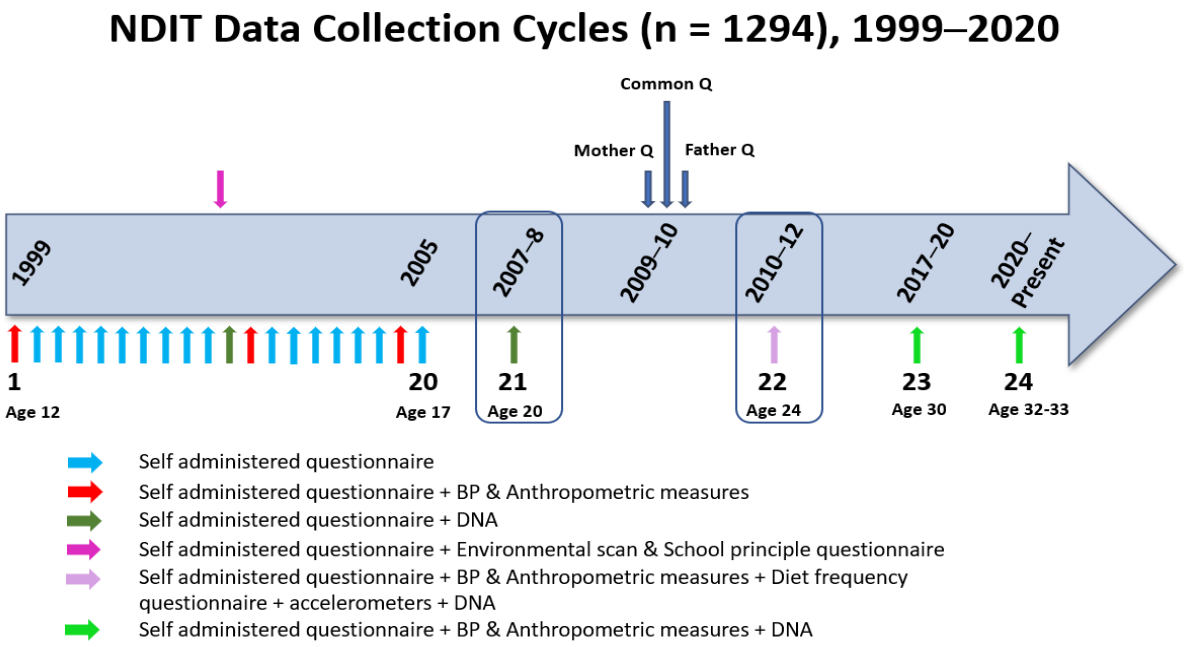


Figure 4. NDIT Data Collection Cycles (n = 1294), 1999–2020

## 4.2 Study Variables

In this thesis, data for the outcome of interest (i.e., depressive symptoms) were drawn from cycle 22. Data on the exposure variables (i.e., PA, SB, sleep) as well as covariates (i.e., age, sex, level of education, earlier depressive symptoms) were drawn from cycle 21 completed approximately four year before cycle 22.

### 4.2.1 Depressive symptoms

The outcome variable, depressive symptoms, was measured in NDIT cycle 22 using the Major Depression Inventory (MDI) (Bech, Rasmussen, Olsen, Noerholm, & Abildgaard, 2001). The MDI is a 10-item diagnostic scale that scores self-reports of DSM-IV and ICD-10 depressive symptomatology (Bech et al., 2001). The MDI includes 12 items in total; items 8 and 10 have two sub-items a and b, and only the highest score of either a or b is retained. Thus, the MDI is functionally a 10-item questionnaire (Bech et al., 2001). In cycle 22, participants completed the MDI questionnaire which inquires about the frequency of depressive symptoms over the previous two weeks. Response options for each item are scored on a 6-point Likert-type scale ranging from 0 “At no time” to 5 “All the time” (see Appendix A for the exact MDI items used in NDIT cycles 21 and 22). The MDI total score ranges between 0 and 50, with higher scores denoting more frequent and severe depressive symptoms. The MDI had a high internal consistency in an earlier study ($\alpha = 0.94$) (Bech et al., 2001). In NDIT cycles 21 and 22, MDI Cronbach’s was $\alpha = 0.88$ and 0.90, respectively. The MDI score is treated as a continuous variable in this thesis.

### 4.2.2 Time Spent in PA

Time spent in PA of differing intensities was measured in NDIT cycle 21 using the short version of the International Physical Activity Questionnaire (IPAQ-SF) (Craig et al., 2017). IPAQ-SF is a 6-item questionnaire that measures time spent in vigorous intensity PA (VPA), moderate intensity PA (MPA), and walking over the last 7 days. Walking was the only type of

light-intensity PA measured in cycle 21, and it was included in this analysis as a proxy for time spent daily in light-intensity PA. Two IPAQ-SF items measure PA at each of vigorous, moderate and light intensities. Time spent in VPA was measured by asking participants: "*During the last 7 days, on how many days did you do vigorous physical activities (heavy lifting, digging, aerobics, fast bicycling) for at least 10 minutes at a time?"* and "*On the days that you did vigorous physical activities, how many minutes did you usually spend per day?*". Time spent in MPA and walking, was measured using similar items. A complete list of the IPAQ-SF used in NDIT cycle 21 is provided in Appendix A. The IPAQ-SF data processing guide (www.ipaq.ki.se, 2005) recommends that activity bouts greater than 3 hours (i.e., 180 minutes) be truncated to allow a maximum of 21 hours (i.e., 1,260 minutes) per week in each activity category. Accordingly, VPA, MPA, and walking values exceeding 180 minutes were truncated to 180 minutes. The average time spent in VPA daily was then calculated using the following formula: Average daily VPA = [(No. of days of VPA during past week) × (No. of minutes of VPA on those days)]/7. The same formula was applied to calculate average daily time spent in MPA and walking. Finally, average VPA daily was added to average MPA daily to obtain the average time spent MVPA daily. IPAQ-SF has a good median test-retest reliability (r = 0.80) and criterion validity correlations against accelerometer-measured data ranged from r = 0.14 to 0.53, with a median of r = 0.30 (Craig et al., 2003). Time spent in MVPA and walking are used as continuous variable (i.e., minutes per day) in this thesis.

### 4.2.3 Time Spent in SB

SB was measured in cycle 21 using four items adapted from a systematic review (Bryant, Lucove, Evenson, & Marshall, 2007), including: "*How many hours of television (including video movies) do you usually watch in a single day?"; "How many hours do you usually spend on a computer in a single day for school or at work?";* "*How many hours do you usually spend on a computer in a single day during your leisure time (playing computer games, using the Internet)?*; and "*How many hours do you usually spend reading (books, magazines, newspapers, homework) in a single day?* Participants recorded the number of hours spent in each behaviour on a usual weekday and on a usual weekend day; they were instructed to: *"Write "0" if none.*

*Write "LT ½" if less than ½ hour*". Average time spent daily in SB was then calculated using the following formula: [(sum of hours per weekday × 5) + (sum of hours per weekend day × 2)]/7. Time calculated in hours was multiplied by 60 to obtain average time spent in SB daily in minutes. Internal consistency, which represents the general level of agreement between the four items used to measure SB in cycle 21, was estimated by Cronbach's ($\alpha = 0.61$). Time spent in SB daily is used as a continuous variable (i.e., minutes per day) in this thesis.

### 4.2.4 Time Spent Sleeping

In NDIT cycle 21, time spent sleeping was measured using two items adapted from the Pittsburgh Sleep Quality Index (PSQI) (Dj, Reynolds, Monk, Berman, & Kupfer, 1989). Participants answered two questions: *"In the past month, at what time did you usually go to sleep at night?*" and "*In the past month, at what time did you usually wake up in the morning?*". Participants reported both "go-to-sleep" and "wake-up" time in a 24-hour format. To convert the 24-hour format into minutes, the first two digits of the 24-hour format were multiplied by 60 and summed with the last two digits. Sleep duration was then calculated using one of two formulas. First, if "wake-up time" > "go-to-sleep time", the formula: ("wake-up time" − "go-to-sleep time") was used. If "wake-up time" < "go-to-sleep time", the formula: ["wake-up time" - ("go-to-sleep time" − 1440)] was used to obtain the average time of sleep daily in minutes. An example of the method used to calculate sleep duration in NDIT cycle 21 is shown in figure 5.

Participant (A) → sleeps at 01:00 and wakes up at 08:00
Participant (B) → sleeps at 23:00 and wakes up at 08:00

Step 1: Converting hours to minutes
participant (A) → sleep-time = 60 , and wake-up-time = 480 minutes
participant (B) → sleep-time = 1380, and wake-up time = 480 minutes

Step 2: Calculating sleep duration
Participant (A) → wake-up-time > sleep-time (480 > 60), so sleep time = 480–60 = 420 minutes
Participant (B) → wake-up-time < sleep-time (480<1380), so sleep time = 480 – ( 1360 –1440), so sleep time = 480 – (–60), so sleep-time = 480 + 60 = 540 minutes

Figure 5. An example of the method used to calculate sleep duration in NDIT cycle 21.

### 4.2.5 Covariates

Multiple confounding factors influence the association between PA, SB and sleep as exposure variables and depressive symptoms as an outcome. Three Directed Acyclic Graphs (DAGs) (Textor, van der Zander, Gilthorpe, Liśkiewicz, & Ellison, 2016) (Appendix B) were developed to identify possible confounders of these associations, one DAG for each exposure variable (PA, SB and sleep) in association with depressive symptoms, based on available evidence (Brunet et al., 2013; Conklin, Yao, & Richardson, 2018; Dinis & Bragança, 2018; Zhai et al., 2015). After examining the DAGs, we decided not to adjust for covariables that are not confounders to the association or those on the causal pathway of the association. Additionally, we selected to address the following potential confounders: age, sex, highest educational level attained, and depressive symptoms in NDIT measured in cycle 21 (prior to measurement of the depressive symptom outcome). Age was calculated based on birthdate and date when the survey cycle 21 questionnaire was completed. Highest educational level attained was considered a valid proxy for socioeconomic status because it is highly correlated with employment and income (Galobardes et al., 2006). Participants responded to: "*How far have you gone in school?*" with response options ranging from attending or graduating from high school, CEGEP/technical school, university with a Bachelor's, Master's or PhD degree or Other. CEGEP refers to pre-college university programs and the term is unique to Quebec. Participants who responded "Other" specified the highest education level that they had attained and, based on their response, were reallocated to another response category. For analysis, participants were categorized into one of three categories: "attended/graduated high school", "attended/graduated CEGEP/technical school", or "attended/graduated university". Baseline depressive symptoms in cycle 21 was included as a covariable because earlier depressive symptoms could be associated with a different profile of movement behaviours (i.e., PA, SB, sleep) as exposure variables with later depressive symptoms as the outcome variable (Lovato et al., 2017; Raudsepp, Vink, & health, 2019; Stavrakakis, de Jonge, Ormel, & Oldehinkel, 2012).

## 4.3 Analytic Sample

Of the 1294 NDIT participants at inception, 858 (66.3%) participated in cycle 22. Of these, nine were missing MDI data in cycle 22 and 62 did not participate in cycle 21 and were then excluded. Of the remaining participants, 12 participants were missing MVPA data, 17 were missing data on walking, 8 were missing data on SB, 3 were missing sleep data, and 1 participant was missing data on highest education level attained and were therefore excluded from the analysis. Finally, an additional 17 participants were excluded due to aberrant value for movement behaviours (i.e., participant reported values greater than 24 hours) and/or discrepant data (e.g., participant reported 0 days doing the activity but then reported hours or minutes doing the activity). Thus, a total of 729 participants (56.3%) of the 1294 participants at inception were retained for analysis (Figure 5). Characteristics of participants retained and not retained for analysis are compared in Table 1.

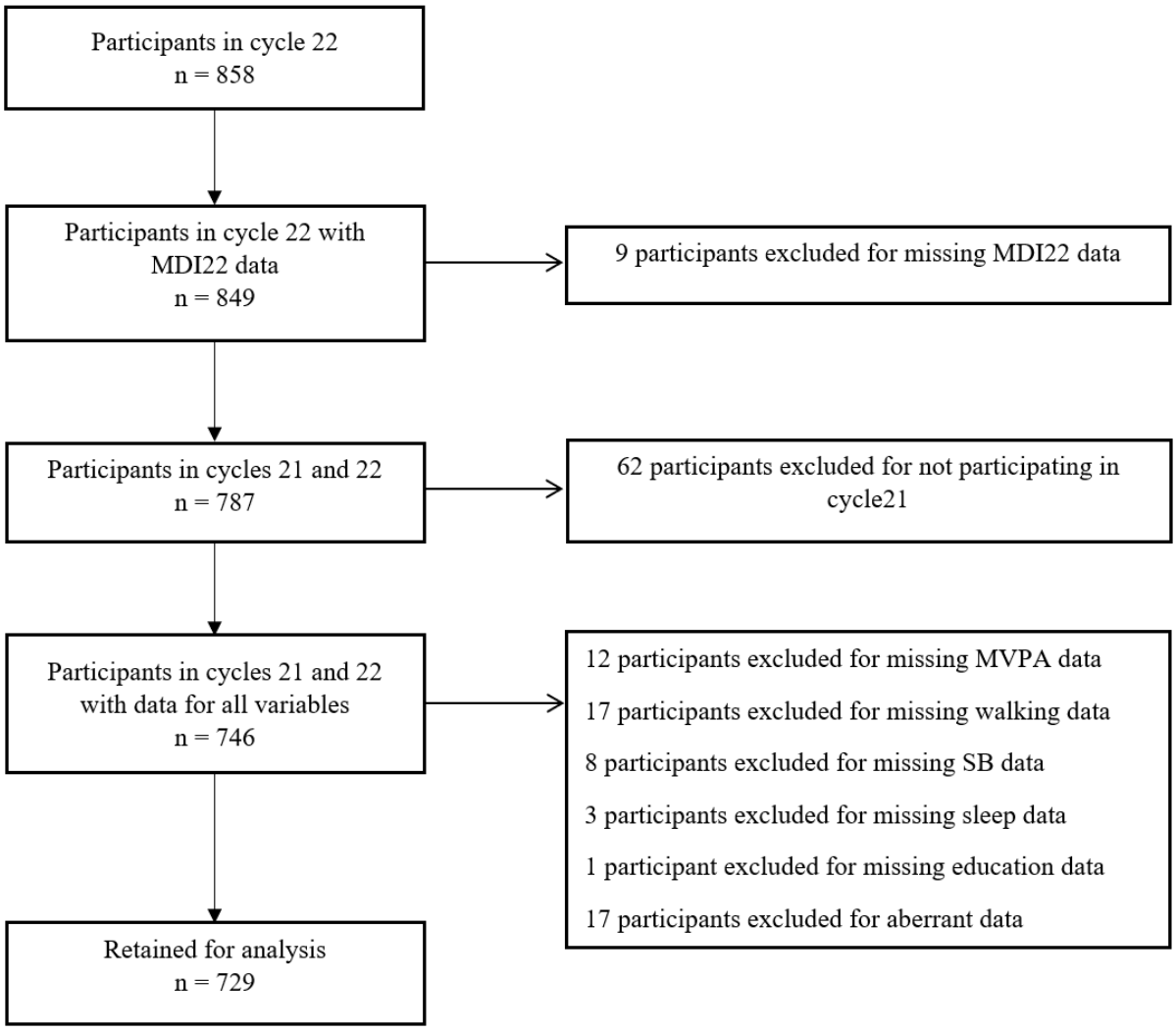


Figure 6. Flowchart describing the derivation of the analytic sample.

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## 4.4 Data Analysis:

### 4.4.1 Compositional Data Analysis (CoDA)

Time spent in MVPA, walking, SB and sleep (i.e., the exposure variables) is examined using a Compositional Data Analysis (CoDA) model based on the principles described by John Aitchison (Aitchison, 1982). Compositional Data Analysis (CoDA) is an analytic method used to examine data when the variables represent parts of a whole (Pawlowsky-Glahn & Buccianti, 2011). The whole is called a *composition,* which comprises a number of *d* parts. These parts are expressed as vectors of proportions or ratios of the whole (Pawlowsky-Glahn & Buccianti, 2011). The sum of the parts always adds up to a constant value and the sum of the proportions adds up to 1 (100%). As a result of having a constant sum, compositional data lie within a constrained space called *Simplex*. The simplex is closed by the sum of proportions of the its parts, and data values inside the simplex are finite and cannot exceed the closure sum.

Time-use within 24-hour period is compositional in nature because time spent daily in any activity always relates to PA, SB or sleep. The sum of time spent daily in PA, SB and sleep always adds up to 24 hours, and the sum of their proportions adds up to 1 (100%). As a consequence, there is perfect multicollinearity between time spent in PA, SB and sleep (Chastin & Palarea-Albaladejo, 2015). The multicollinearity between movement behaviours necessarily means that an increase in time spent in one behaviour is associated with an exact-same decrease in time spent in one or more of the other behaviours, so that their sum always attains 24 hours (Chastin & Palarea-Albaladejo, 2015). Because of the co-dependence between time spent daily in PA, SB and sleep, standard analytic models such as multiple linear regression (which assume independence between exposure variables) may produce flawed results (Chastin & Palarea-Albaladejo, 2015; Pearson, 1897). A major advantage of applying CoDA in the current analysis is that it allows use of a multiple linear regression model to examine the association between the proportions of time spent daily in PA, SB and sleep and depressive symptoms, controlling for covariates, while taking the multicollinearity of time spent in different movement behaviours within the 24-hour period into account. Another advantage of CoDA is that it applies to time-use data of any period and not necessarily an exact 24-hour period (Chastin & Palarea-

Albaladejo, 2015; Pedišić et al., 2017). As long as data are available for the same behaviours for all participants and are normalized to the same scale, the relative proportions of the behaviours investigated are maintained and incorporate all the information needed to conduct the analysis (Chastin & Palarea-Albaladejo, 2015)

CoDA relies heavily on log transformation of the data. Thus, it is necessary to treat zero values in a compositional dataset before applying CoDA (Aitchison, 1982; Pawlowsky-Glahn & Buccianti, 2011). Zero values in time-use data are generally considered as rounded zeros which are only reported as zero because they fall below a certain detection limit (Pawlowsky-Glahn & Buccianti, 2011). In our dataset, PA was measured using the IPAQ-SF questionnaire, which has a detection limit of 10 minutes in each PA session. Bouts of time spent in MVPA and walking between 0-9 minutes are reported as zero in the IPAQ-SF questionnaire. Thus, zero values in MVPA and walking are considered as rounded zeros and are treated accordingly. We used the function multRepl() in R package zCompositions to apply a simple multiplicative imputation method to treat zero values (J. Palarea-Albaladejo, J. A. Martín-Fernández, & C. I. L. Systems, 2015a). This imputation method replaces a variable rounded to zero in a vector by a value equal to 65% of the detection limit of that variable. In our analysis, the imputation value was calculated based on the 10-minute per week detection limit in the IPAQ-SF questionnaire. This detection limit was divided by 7 to obtain a value of 1.42 minutes which represents the daily detection limit. Then, 65% of this daily detection limit was estimated to obtain a final imputation value of 0.93. The newly imputed value is multiplied by the other non-zero values in the vector. Then the product is substituted from each value to maintain the original relative proportions of other variables (Martín-Fernández, Barceló-Vidal, & Pawlowsky-Glahn, 2003). This simple multiplicative imputation method is especially effective when the proportion of zeros in a dataset does not exceed 10% of values in the data matrix (Pawlowsky-Glahn & Buccianti, 2011). This is the case in our dataset, wherein there are 253 zeros representing 8.7% of the total values of MVPA, walking, SB and sleep (2,916). The aim of this imputation technique is to replace zeros in a variable while maintaining the relative proportions of other variables. Maintaining the original relative proportions is essential, since proportions of components, rather than their absolute values, are the only parts that carry relevant information

in any given compositional dataset (Chastin & Palarea-Albaladejo, 2015). As recommended in the literature, a sensitivity analysis using a different imputation method such as log-normal multiplicative replacement was conducted to ensure that the imputation method applied did not cause any data distortion (Martín-Fernández & Thió-Henestrosa, 2006).

Following treatment of zeros in the dataset, all movement behaviours values were normalized to their compositional form inside the simplex space. Normalization is achieved by converting movement behaviour values for each participant into proportions of their total sum. Inside the constrained simplex space, the sum of proportions of sleep, SB, walking and MVPA for each participant is always constant and equals 1 (100%) (Pawlowsky-Glahn & Buccianti, 2011). This process of data normalization into compositional form is performed using the function acomp() in the R package "compositions" (Boogaart, Tolosana-Delgado, & Bren, 2020).

Since compositional data are constrained in the simplex space, standard descriptive statistics such as the arithmetic mean are not useful in describing the data. Instead, a better measure of central tendency for compositional data is the compositional geometric mean (Chastin & Palarea-Albaladejo, 2015; Pawlowsky-Glahn & Buccianti, 2011). The compositional geometric mean is computed by first, calculating the geometric mean of each behaviour in the dataset. Then, the resulting vector is normalized to the same scale used to normalize the dataset. As such, the 4 geometric means obtained were converted to proportions of their sum, wherein the sum of their proportions adds up to 1 (i.e., similar to our compositional dataset). Calculating the compositional geometric mean was performed using the function mean() in R after converting the dataset into Aitchison composition class "acomp". Similarly, variance of single parts inside the composition is meaningless because it does not account for the co-dependence between parts. Thus, variation inside the simplex is better described using a compositional variation matrix. A variation matrix is a symmetrical matrix that describes co-dependence between parts inside the simplex space by estimating the variances in logarithms of all pairwise ratios of all parts (Chastin & Palarea-Albaladejo, 2015; Pawlowsky-Glahn &

Buccianti, 2011). The variation matrix for our dataset was calculated using the variation() function in the package "compositions" (Boogaart et al., 2020).

### 4.4.2 Multiple Linear Regression Model for Compositional Data

While CoDA effectively solves the technical issue of multicollinearity in time-use data, compositional data are constrained in the simplex space. Finite data in a constrained space cannot be used in a standard regression analysis which only applies to data in real space that can vary freely between [-∞, ∞] (Chastin & Palarea-Albaladejo, 2015). To apply compositional data within a regular regression analysis model, compositional data must be transformed from their constrained simplex space to corresponding values in the real space using a log-ratio transformation method (Aitchison, 1982; Pawlowsky-Glahn & Buccianti, 2011). Multiple log-ratio transformation methods exist. Isometric log-ratio (ilr) transformation is the recommended method for time-use data (Chastin & Palarea-Albaladejo, 2015; Dumuid, Stanford, Martin-Fernández, et al., 2018). The isometric log-ratio (ilr) transformation method converts *d* parts of a composition from simplex space into corresponding equivalent *d*-1 coordinates in real space. The created ilr coordinates in real space can then be applied within a standard regression model and can be freely back-transformed to simplex space for further interpretation, if needed, after regression analysis (Chastin & Palarea-Albaladejo, 2015; Pawlowsky-Glahn & Buccianti, 2011). In our movement behaviours composition, there are *(d* = 4) parts representing the time spent in MVPA, walking, SB and sleep. Each part can be transformed to the real space using a set of 3 (*d*-1) ilr coordinates. The first coordinate of each behaviour represents the proportion of this behaviour in relation to the proportions of the other behaviours. The second and the third coordinates represent the relation between the proportions of the remaining behaviours (Chastin & Palarea-Albaladejo, 2015). These ilr coordinates are values in real space that carry the exact information about the position and direction of values inside the simplex space (Chastin & Palarea-Albaladejo, 2015). We used the ilr() function in R package "compositions" to create ilr coordinates for our dataset.

Four different sets of ilr coordinates were created, each representing the real space equivalent for MVPA, walking, SB and sleep values. Each set of behaviour ilr coordinates was fitted in a separate multiple linear regression model to examine the association between the first ilr coordinate of this behaviour, representing the proportion of this behaviour relative to the other behaviours proportions, and depressive symptoms while accounting for the multicollinearity between behaviours and controlling for potential confounders of the association (See Appendix D for a complete compositional data analysis guide including equations used for creating ilr coordinates for movement behaviours).

A group of single regression models were fitted to explore the simple association between time spent in each of MVPA, walking, SB and sleep in cycle 21 and depressive symptoms in cycle 22. These models provide information on the ability of each behaviour to individually predict depressive symptoms. Understanding the ability of each behaviour to predict depressive symptoms helps interpret the results of the log-ratio multiple regression models that take multicollinearity between movement behaviours into account.

A log-ratio multiple linear regression model was used to examine the association between time spent in MVPA, walking, SB and sleep in cycle 21, using their ilr coordinates, and depressive symptoms in cycle 22, while controlling for age, sex, highest education level attained and depressive symptoms in cycle 21. The fitted model is interpreted in a way similar to a regular multiple regression model including the model $R^2$, coefficients, intercept and p-values. It is important to note that there are 3 different coefficients for the 3 ilr coordinates in each model. In fact, the coefficient of the first ilr coordinate of a behaviour, which represents the proportion of this behaviour in relation to the other behaviours, is the only coefficient that can be interpreted meaningfully. The coefficient of the first ilr coordinate of a certain behaviour represents the ability of the proportion of time spent in this behaviour relative to the other behaviours to predict depressive symptoms (Chastin & Palarea-Albaladejo, 2015). It is important to note that use of isometric log-ratio transformation ensures that the order of parts during transformation does not affect the end result. In addition, the log ratio of proportions of

behaviours is equal even when the numerator and denominator are inversed. As a result, the 4 multiple linear regression models using the 4 sets of ilr coordinates, representing the 4 types of movement behaviours (MVPA, walking, SB, sleep), have the same model fit with the exact same $R^2$, P-values, intercept and covariables coefficient values (Chastin & Palarea-Albaladejo, 2015). The only difference between the models is the coefficients of the 3 ilr coordinates of each set and these are interpreted as previously described.

### 4.4.3 Compositional Isotemporal Reallocation Model

Our second objective was to estimate change in depressive symptoms with reallocation of specific number of minutes between movement behaviours. Although ilr coordinates help fit compositional data in a standard multiple regression model, the capacity of the model to explain the effect size of the association between the exposure and outcome variables and to address the second objective is limited. For example, our time-use regression model will fail to explain whether a change in the outcome of depressive symptoms is due to an increase in the time spent in one behaviour or the corresponding decrease in the other behaviours. Thus, a compositional isotemporal reallocation model was used to estimate the effect sizes. This model allows for estimating change in absolute values of depressive symptoms after reallocating a specific amount of time from one specific behaviour to another, while keeping all other variables constant.

In our analysis, we used one of the fitted multiple linear regression models to predict a depressive symptoms value around a certain point inside the simplex space of our compositional dataset. We selected the compositional mean values for MVPA, walking, SB and sleep, expressed in ilr coordinates, as starting point for prediction because it represents the central point of our compositional dataset. We then reallocated different amounts of time from one movement behaviour to another around the compositional mean. The new values after reallocation of time were used as a composition, expressed in ilr coordinates, to predict a new depressive symptoms score, while covariables remained constant. The difference between the two predictions represents the predicted absolute depressive symptoms score after the

reallocation of time from one behaviour to another around the compositional mean. The same model was repeated between all pairs of behaviours. We created a change in prediction matrix which represents depressive symptoms values relative to the reallocation of different amounts of time equal to 10, 15, 20, 25 and 30 minutes between all behaviours. We selected 10 minutes as a starting amount of time reallocation because it is the least amount of time that has proven to have health benefits (Chastin et al., 2015; Haskell et al., 2007). We added 5-minute increments of time reallocation up to 30 minutes, which resembles the recommended amount of time daily over 5 days per week to achieve an overall goal of 150 minutes of MVPA weekly. It is important to note that any of the 4 fitted log-ratio multiple linear regression models can be used to calculate the predictions. The results will be the same across models since all the models have the same $R^2$, p-values, intercept and covariables coefficients.

All analyses were conducted using R software version 4.0.2 (R Core Team, 2020) and RStudio version 1.3.1056 (RStudio Team, 2020). Zero values in the dataset were imputed using R package "zCompositions" (Palarea-Albaladejo et al., 2015a). Compositional data analysis (CoDA) was conducted using R package "compositions" (Boogaart et al., 2020). Analysis of variance for linear regression was conducted using R package "car" (Fox & Weisberg, 2019). An example of the R code used for CoDA analysis and the compositional isotemporal reallocation model is included in Appendix E.

### 4.4.4 Sensitivity Analysis

A sensitivity analysis was conducted to ensure that the simple multiplicative replacement method used to replace zero values in our compositional dataset did not distort our data and mislead the results (Pawlowsky-Glahn & Buccianti, 2011). For this sensitivity analysis we used the function multLN() of the same R package (J. Palarea-Albaladejo, J. A. J. C. Martín-Fernández, & I. L. Systems, 2015b). The function multLN() imputes left-censored compositional values by the estimated geometric mean of the values below the corresponding limit of detection or censoring threshold (Palarea-Albaladejo et al., 2015b). Similar to the simple multiplicative imputation, multLN() applies a multiplicative adjustment to preserve the

multivariate compositional properties of the samples, thus maintaining the relative proportions of the other variables which is the relevant part of any compositional dataset (Chastin & Palarea-Albaladejo, 2015). Following the imputation, a set of ilr coordinates was created for the compositional values inside simplex space to obtain equivalent values in real space. Those ilr coordinates were then fitted in log-ratio multiple regression model to predict depressive symptoms while controlling for age, sex, highest education level and baseline depressive symptoms (i.e., similar to the model fitted after using the simple multiplicative imputation method). The two log-ratio multiple regression models fitted using ilr coordinates created after treating zero values using both imputation methods were compared to ensure reliability of results.

## 4.5 Ethical Considerations

The NDIT study, from which data for this thesis were drawn, has received ethics approvals from the Montreal Department of Public Health Ethics Review Committee, the McGill University Faculty of Medicine Institutional Review Board, the Ethics Research Committee of the Centre de Recherche du Centre Hospitalier de l'Université de Montréal and the ethics committee at the University of Toronto (see Appendix C for copies of ethics approval certificates). In addition, all NDIT participants provided assent and one of their parents or their legal guardians signed a consent form before participation. The Principal Investigator visited each study school prior to the first data collection to describe the project in detail to teachers and students and provide more information in a question-and-answer session (O'Loughlin et al., 2015).

# Chapter 5: Results

## 5.1 Contributions to Manuscript Preparation

This chapter includes a manuscript entitled: "*A time-use compositional analysis of the association between movement behaviours and depressive symptoms in young adults"*. The journal targeted for publication is the Applied Physiology, Nutrition, and Metabolism (APNM) journal. As first author, the candidate performed all tasks related to manuscript preparation including defining the study objectives, overviewing the literature, conducting data analysis and writing the manuscript. Drs. Jennifer O'Loughlin and Isabelle Doré supervised this project, provided the NDIT data, participated in analytic decisions, and reviewed and edited the manuscript.

## 5.2 Manuscript

**Title**: A time-use compositional analysis of the association between movement behaviours and depressive symptoms in young adults

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**Abstract**

**Background**: Depression is a growing concern among young adults. Movement behaviors including physical activity (PA), sedentary behaviours (SB) and sleep are modifiable risk factors for depression. Understanding whether time spent daily in PA, SB and sleep is associated with depressive symptoms in young adults may inform public health interventions that aim to prevent depression. Our objectives were: (i) to estimate the association between time-use in movement behaviors (i.e., the proportion of time during a 24-hour period spent in each of moderate-to-vigorous intensity PA (MVPA), walking (i.e., a proxy for light intensity PA), SB and sleep) and depressive symptoms in young adults; and (ii) to estimate change in depressive symptoms with reallocation of time-use across pairs of movement behaviours. **Methods**: Data were drawn from the Nicotine Dependence in Teens (NDIT) study, an ongoing longitudinal study that recruited 1294 7$^{th}$ grade students in 10 secondary schools in Montreal, Canada. Data for this analysis were collected in self-report questionnaires at ages 20 and 24. The association between time-use in movement behaviors and depressive symptoms was estimated using time-use compositional analysis. Change in depressive symptoms was estimated using compositional time-reallocation models. **Results**: There was no association between time-use in MVPA (p=0.273), walking (p=0.861), SB (p=0.723) or sleep (p=0.948) and depressive symptoms. There was an approximate 3% increase in depressive symptoms after reallocating 15 minutes from MVPA to SB, and an approximate 1% reduction in depressive symptoms after reallocating 15 minutes from SB to MVPA. However, these changes were non-significant. **Conclusion**: Time-use in movement behaviors was not associated with depressive symptoms in young adults. Replication of our findings is needed in larger datasets with a wider range of ages before the public health implications of our findings are considered.

**Keywords**: Physical Activity, Sedentary Behaviours, Sleep, Youth, Depression, Compositional Analysis

## Introduction

Depression is the most common mental illness – 322 million people worldwide have depression (World Health Organization, 2017). Among all age groups in Canada, young persons between ages 15 and 24 years have the highest prevalence of mood disorders (Statistics Canada, 2013). In 2013, 7% of Canadian youth reported having depression in the past 12 months, and young women were twice as likely as young men to report depression (12% vs 5%) (Canadian Mental Health Association, 2019). Young people who experience depression are at higher risk of mental illness as adults - more than 50% who have an episode of major depression experience a recurrence (Lewinsohn, Rohde, Klein, Seeley, & Psychiatry, 1999; Sabiston et al., 2016). Despite its profound impact on health and social life, depression is under-diagnosed in Canada (Pelletier et al., 2017) and many individuals with depression are untreated. Thus, it is important to better understand modifiable risk factors for depressive symptoms in young adults to inform preventive public health interventions.

Movement behaviours such as physical activity (PA), sedentary behaviours (SB) and sleep are modifiable risk factors for depressive symptoms. Higher levels of PA are associated with lower levels of depressive symptoms in young adults (Brunet et al., 2013), and there appears to be a dose-response association such that longer duration and more intense PA (e.g., moderate-to-vigorous intensity PA (MVPA)) compared to light intensity PA, is associated with better depression outcomes (Bailey et al., 2018). However, whether the association between PA and depression is causal in young adults is unknown since few longitudinal studies explore this link in healthy young adults specifically and, in those that do, follow-ups tend to be of relatively short duration (Biddle et al., 2018). Higher levels of SB are generally associated with poorer mental health outcomes including depression (Suchert et al., 2015). However, the effect of SB on depressive symptoms is not always negative. In fact, time spent in SB has a curvilinear u-shaped association with depressive symptoms, and students who spend moderate amounts of time using the Internet or playing video games report lower depressive symptoms (Durkin & Barber, 2002; Kim, 2012; Suchert et al., 2015). In youth, maintaining sleep duration between 6-8 hours daily is associated with better emotional regulation and fewer depressive symptoms compared to shorter or longer sleep durations (Chaput et al., 2016). Sleep deprivation (i.e., ≤6

hours of sleep per day) is associated not only with depressive symptoms, but also with suicidal ideation in youth (Roberts & Duong, 2014), and longer sleep duration is associated with more depressive symptoms in patients with major depression (Lorenz, Sander, Ivanova, & Hegerl, 2020).

Although PA, SB and sleep each have independent associations with depressive symptoms, the recent literature suggests that their effects may be intertwined. More specifically, in 2007, Tremblay et al. suggested that because these three behaviors are on the same movement continuum, balancing time spent daily between PA, SB and sleep is needed to achieve optimal health (Tremblay et al., 2007). Additionally, time spent in PA, SB and sleep within the 24-hour period is co-dependant because an increase in time spent in one behaviour is necessarily associated with a decrease in time spent in one or both of the other behaviours. Zhai et al. observed that an increase in SB time may come at the expense of PA, which is known to regulate brain chemicals associated with mental illness. By decreasing PA time, SB may increase the risk of depressive symptoms (Zhai et al., 2015). Similarly, Chaput et al. suggested that long sleep duration may come at the expense of time spent in PA, which can negatively influence a variety of health outcomes (Chaput et al., 2016). Reflecting this recent literature, the Canadian 24-hour movement guidelines for adults ages 18 to 64 newly released in 2020, included recommendations on the optimum amount of PA, SB and sleep daily (i.e., 150 minutes per week, 8 hours or less daily, 7–9 hours daily, respectively) highlighting the importance considering PA, SB and sleep together in examining their associations with health outcomes (Ross et al., 2020).

Despite increased understanding of their co-dependence, most studies to date examine only one movement behaviour in association with depressive symptoms, and studies that include two movement behaviours generally do not account for possible co-dependence of time spent in the two behaviors during a 24-hour period. Additionally, most studies are cross-sectional, and few investigate depressive symptoms over the long-term in young adults. The objectives of this current study were: (i) to estimate the association between time-use in movement behaviors (i.e.,

the proportion of time during a 24-hour period spent in each of moderate-to-vigorous intensity PA (MVPA), walking (i.e., a proxy for light intensity PA), SB and sleep) and depressive symptoms in young adults; and (ii) to estimate change in depressive symptoms with reallocation of time-use across pairs of movement behaviours. Increased understanding of these associations could inform public health interventions that aim to optimize time spent in PA, SB and sleep with the goal of preventing depressive symptoms in young adults.

## Methods

Data were drawn from the Nicotine Dependence in Teens (NDIT) study, a 20-year longitudinal investigation of 1294 grade 7 students recruited in 1999–2000 in 10 high schools in Montreal, Canada (O'Loughlin et al., 2015). A school-based sampling strategy was used to recruit grade 7 students in 10 Montreal-area high schools purposively selected to include a mix of French- and English-language schools, urban, suburban, and rural schools, and schools located in neighbourhoods with high, moderate and low socioeconomic status (O'Loughlin et al., 2015). In cycle 21 in 2007–08 self-report questionnaires were mailed to participants (then age 20 years on average) at home or completed online. In cycle 22 in 2011–12, NDIT participants (i.e., then age 24 years on average) completed self-report questionnaires administered in the NDIT research office (O'Loughlin et al., 2015). Data for the outcome of interest (i.e., depressive symptoms) were drawn from cycle 22, while data on the exposure variables (i.e., MVPA, walking, SB, sleep) and covariates (i.e., age, sex, highest education level attained, earlier depressive symptoms) were drawn from cycle 21. NDIT study has received ethics approvals from the Montreal Department of Public Health Ethics Review Committee, the McGill University Faculty of Medicine Institutional Review Board, the Ethics Research Committee of the Centre de Recherche du Centre Hospitalier de l'Université de Montréal and the University of Toronto.

## Study Variables

Depressive symptoms were measured in NDIT cycle 21 and 22 using the Major Depression Inventory (MDI) (Bech et al., 2001). The MDI is a 10-item diagnostic scale that

scores self-reports of DSM-IV and ICD-10 depressive symptomatology (Bech et al., 2001). Participants completed the MDI questionnaire which inquires about the frequency of depressive symptoms over the previous two weeks. Response options for each item were on a 6-point Likert-type scale ranging from "At no time" scored 0 to "All the time" scored 5. MDI scores range between 0 and 50, with higher scores denoting more frequent and severe depressive symptoms. The MDI had high internal consistency in an earlier study ($\alpha = 0.94$) (Bech et al., 2001) and in NDIT cycle 21 ($\alpha = 0.88$) and cycle 22 ($\alpha = 0.90$). In this analysis, the MDI score is treated as a continuous variable.

Time spent daily in MVPA and walking was measured using the short version of the International Physical Activity Questionnaire (IPAQ-SF) (Craig et al., 2017). IPAQ-SF is a 6-item questionnaire that measures time spent in vigorous intensity PA, moderate intensity PA, and walking over the last 7 days. Time spent in vigorous PA is measured in two items: "*During the last 7 days, on how many days did you do vigorous physical activities (heavy lifting, digging, aerobics, fast bicycling) for at least 10 minutes at a time?"* and "*On the days that you did vigorous physical activities, how many minutes did you usually spend per day?*". Time spent in moderate PA and walking, is measured using similar items. As per the IPAQ-SF data processing guide (www.ipaq.ki.se, 2005) activity bouts greater than 180 minutes were truncated to allow a maximum of 1260 minutes per week in each activity category. Average time spent in vigorous intensity PA daily was then calculated using the following formula: Average daily vigorous intensity PA = [(no. of days of vigorous pa during past week) × (no. of minutes of vigorous PA on those days)]/7. The same formula was applied to calculate average daily time spent in moderate intensity PA and walking. Average vigorous and moderate intensity PA times were summed to obtain average time spent in MVPA daily. IPAQ-SF has good median test-retest reliability ($\rho = 0.80$) and criterion validity correlations against accelerometer measured PA data ranged from 0.14 to 0.53, with a median of 0.30 (Craig et al., 2003).

SB were measured in cycle 21 using four items adapted from a systematic review (Bryant et al., 2007), including: "*How many hours of television (including video movies) do you usually*

*watch in a single day?"; "How many hours do you usually spend on a computer in a single day for school or at work?";* "*How many hours do you usually spend on a computer in a single day during your leisure time (playing computer games, using the Internet)?*; and "*How many hours do you usually spend reading (books, magazines, newspapers, homework) in a single day?* Participants recorded the number of hours spent in each behaviour on a usual weekday and on a usual weekend day; they were instructed to: *"Write "0" if none. Write "LT ½" if less than ½ hour*". Average time spent daily in SB was then calculated using the following formula: [(sum of hours per a weekday × 5) + (sum of hours per a weekend day × 2)]/7. Time calculated in hours was multiplied by 60 to obtain average time spent in SB daily in minutes.

In NDIT cycle 21, participants reported sleep duration in two items adapted from the Pittsburgh Sleep Quality Index (PSQI) (Dj et al., 1989): *"In the past month, at what time did you usually go to sleep at night?*" and "*In the past month, at what time did you usually wake up in the morning?*". Participants reported both go-to-sleep time and wake-up time in a 24-hour format. To convert the 24-hour format into minutes, the first two digits of the 24-hour format were multiplied by 60 and summed with the last two digits. Sleep duration was then calculated using one of two formulas. First, if wake-up time > go-to-sleep time, the formula (wake-up time – go-to-sleep time) was used. If wake-up time < sleep time, the formula [wake-up time – (go-to-sleep time – 1440)] was used to obtain the average time of sleep daily in minutes. In this analysis, time spent in MVPA, walking, SB and sleep was considered as continuous variables.

Potential confounders of the association between MVPA, walking, SB and sleep and depressive symptoms included age, sex, highest education level attained and previous depressive symptoms in cycle 21 (Brunet et al., 2013; Conklin et al., 2018; Dinis & Bragança, 2018; Zhai et al., 2015);(Lovato et al., 2017; Raudsepp et al., 2019; Stavrakakis et al., 2012). All measures of potential confounders were drawn from cycle 21. Highest educational level attained was considered a valid proxy indicators of socioeconomic status because it affects employment and income (Galobardes et al., 2006). Participants responded to: "*How far have you gone in school?*" with response options ranging from attending or graduating from high

school, Collège d'enseignement général et professionnel (i.e., CEGEP)/technical school, university with bachelor's, Master's or PhD degree or Other. CEGEPs in Quebec offer both pre-college university programs and technical training. Participants were categorized according to their response into one of three categories: "attended/graduated high school", "attended/graduated CEGEP/technical school", or "attended/graduated university".

**Data Analysis**

To avoid large standard errors, our analytic approach takes multicollinearity in time spent in PA, SB and sleep within a 24-hour period into account. Large standard errors in a regression model suggest that the estimates vary greatly across samples, rendering interpretation of the estimates and their significance more difficult (Vatcheva, Lee, McCormick, & Rahbar, 2016). Compositional Data Analysis (CoDA) is an analytic method that considers data in which the variables studied represent parts of a whole (Pawlowsky-Glahn & Buccianti, 2011). Time-use is compositional in nature because time spent daily in any movement behaviour always relates to one of PA, SB or sleep. Specifically, the sum of time spent daily in PA, SB and sleep always adds up to 24 hours, and the sum of their proportions adds up to 1 (100%). CoDA permits including PA, SB and sleep in a regression model while accounting for their multicollinearity.

CoDA incorporates five steps. Step 1 involves converting movement behaviours into their compositional form that lie in a constrained space called the "simplex space". In Step 2, zero values in the compositional dataset are treated before conducting CoDA. In Step 3, ratios of movement behaviours in the simplex space are transformed into equivalent isometric log-ratio (ilr) coordinates in real space, for use in standard regression models. In Step 4, compositional multiple regression models that use ilr coordinates of movement behaviours, are fitted in the regression model. In Step 5, a compositional isotemporal reallocation model is developed to estimate change in depressive symptoms with reallocation of time between movement behaviours. The following paragraphs describe each step in detail.

Step 1 involved converting movement behaviours into their compositional form, which is achieved by normalizing movement behaviours values for each participant into ratios of their sum that add up to 1. Data in their compositional form lie in a constrained space called the simplex space, in which ratios of data may only vary between 0 and 1. Data were normalized to their compositional form inside the simplex space by converting movement behaviour values for each participant into proportions of their total sum. Inside the constrained simplex space, the sum of the proportions of sleep, SB, walking and MVPA for each participant is always constant and equals 1 (Pawlowsky-Glahn & Buccianti, 2011).

Zero values are treated in Step 2. CoDA relies on log-ratios in many of its mathematical equations, so it is essential to treat zero values in a compositional dataset before proceeding with CoDA. Zero values in our PA data are generally considered as rounded zeros (Pawlowsky-Glahn & Buccianti, 2011), which are reported as zero because they fall below the detection limit of 10 minutes per week in the IPAQ-SF questionnaire. We applied a simple multiplicative replacement technique replacing zero values in the PA variables based on the detection limit (Palarea-Albaladejo et al., 2015a). Zero values in the MVPA and walking variables were replaced by 0.93, which represents 65% of the detection limit in the IPAQ-SF tool at 10 minutes per week (i.e., 1.42 minute/day). A sensitivity analysis using the log-normal replacement method was conducted to ensure that the imputation did not cause any data distortion (Martín-Fernández & Thió-Henestrosa, 2006).

Compositional geometric means (i.e., which better represent central tendency in compositional data than arithmetic means) were calculated by estimating the geometric mean of each behaviour in the dataset, and then the created vector of values was normalized to the same scale of the compositional dataset so that their sum equals 1 (Chastin & Palarea-Albaladejo, 2015). For comparison purposes, we calculated and included the standard arithmetic means for movement behaviours. Dispersion between behaviours inside the simplex space was described using a variation matrix which denotes the co-dependence between parts inside the simplex space by estimating the variances in logarithms of all pairwise ratios of all parts (Chastin &

Palarea-Albaladejo, 2015; Pawlowsky-Glahn & Buccianti, 2011). The closer the value to zero between two behaviours inside the variation matrix, the higher the co-dependence between the proportions of those two behaviours.

In Step 3, ratios of movement behaviours in the simplex space were transformed into equivalent isometric log-ratio (ilr) coordinates in real space that can be used in standard regression models. While CoDA effectively solves the technical issue of multicollinearity in time-use data, compositional data are in the constrained simplex space and cannot be fitted in standard regression analysis, which only applies to numerical values in real space that can vary freely between [-∞, ∞] (Chastin & Palarea-Albaladejo, 2015). As such, data were transformed from the simplex space to an equivalent form in real space using the isometric log-ratio (ilr) transformation technique. Specifically, a set of ilr coordinates was created for each behaviour in the composition with each set composed of vectors of three ilr coordinates. The first coordinate of each behaviour represents the proportion of this behaviour in relation to the proportions of the other behaviours. The second and the third coordinates represent the relation between the proportions of the remaining behaviours (Chastin & Palarea-Albaladejo, 2015) (See CoDA guide in Appendix D).

In Step 4, compositional multiple regression models that use the ilr coordinates of movement behaviours, were fitted to examine the association between time spent in MVPA, walking, SB and sleep, and depressive symptoms (measured in cycle 22) while controlling for age, sex, highest education level attained and depressive symptoms (measured in cycle 21). We included the coefficient of the first ilr coordinate of each behaviour in each model to examine the association between the proportion of time spent in this behaviour and depressive symptoms (Chastin & Palarea-Albaladejo, 2015). Statistical significance of the associations in the ilr regression models were examined using p-values (i.e., $p<0.05$) (Chastin & Palarea-Albaladejo, 2015).

In Step 5, a compositional isotemporal reallocation model, adapted from the method described by Dumuid et al. (Dumuid, Stanford, Pedišić, et al., 2018), was conducted to quantify the effect size of the association by estimating the change in depressive symptoms with reallocation of different amounts of time between pairs of behaviours. First, one of the fitted log-ratio multiple regression models was used to estimate a base depressive symptoms score using MVPA, walking, SB and sleep values equal to the compositional mean (i.e., the estimated base depressive symptom score at the compositional mean (95% prediction interval) = 9.04 (-4.25, 22.89)). Second, amounts of time equal to 10, 15, 20, 25 and 30 minutes were reallocated between each pair of behaviours around the compositional mean while the rest of variables were held constant. We selected 10 minutes as a starting amount of time reallocation because it is the least amount of time associated with health benefits (Chastin et al., 2015; Haskell et al., 2007). We added 5-minute increments of time reallocation up to 30 minutes, which resembles the recommended amount of time daily over 5 days per week to achieve an overall goal of 150 minutes of MVPA weekly. Third, the proportions of time that resulted after time reallocation were used as ilr coordinates to estimate new depressive symptoms scores. Fourth, the change in depressive symptoms score after time reallocation was calculated using the formula: (estimated score after time reallocation – estimated base score at the compositional mean). Finally, all values representing the change in depressive symptoms estimates with time reallocation were collected in "change in prediction" matrices (Supplementary Table 3). Values in the table show the change in depressive symptoms estimates after reallocating time from behaviours in the column to behaviours in the rows. Negative values in the table indicate a decrease in the depressive symptoms score with time reallocation. Positive values indicate an increase in the depressive symptoms scores with time reallocation.

All analyses were conducted using R software version 4.0.2 (R Core Team, 2020) and RStudio version 1.3.1056 (RStudio Team, 2020). Zero values in the dataset were imputed using R package "zCompositions" (Palarea-Albaladejo et al., 2015a). Compositional data analysis (CoDA) was conducted using R package "compositions" (Boogaart et al., 2020). An example of the R code used for CoDA analysis and the compositional isotemporal reallocation model is included in Appendix E.

**Results**

Of the 1294 NDIT participants at inception, 729 (56.3%) were retained for analysis. Among those not retained, 436 participants did not participate in NDIT cycle 22, 112 were missing data on the outcome, exposures or covariates and 17 were excluded due to aberrant values for movement behaviours (i.e., the participant reported values greater than 24 hours) and/or discrepant data (e.g., the participant reported 0 days doing the activity but then reported hours or minutes doing the activity). Table 1 compares the characteristics of participants retained and not retained for analysis. Compared to those not retained, retained participants were younger on average, higher proportions were female and born in Canada, relatively more had university-educated mothers, had attended/graduated CEGEP/technical school, had attended/graduated university and they spent less time in SB on average. There was no statistically significant difference between participants retained and not retained in language, depressive symptoms or time spent in MVPA, walking or sleep. On average, participants retained for analysis spent 39.0 minutes in MVPA daily, 33.3 minutes walking daily, 413.6 minutes (i.e., 6.9 hours) in SB daily, and 501.1 minutes (i.e., 8.4 hours) sleeping (in cycle 21). The mean depressive symptoms score among participants retained for analysis was 8.4 (in cycle 22).

A comparison between the compositional geometric mean and standard arithmetic mean represented as percentages of time spent in MVPA, walking, SB and sleep, after applying CoDA, is shown in Table 2. The compositional geometric mean is a more accurate measure of central tendency in compositional datasets (Chastin & Palarea-Albaladejo, 2015; Pawlowsky-Glahn & Buccianti, 2011). As such, the arithmetic means over-estimates the percentage of time spent in MVPA and walking (4% and 3.4%, respectively) compared to the compositional mean (1.2% and 1.7%, respectively). Further, the arithmetic means under-estimate the percentage of time spent sleeping (53.1%) compared to the compositional mean (56.7%), while percentage of time spent in SB is equivalent (39.5% vs 40.4%). The compositional variation matrix which describes variability in the data inside the simplex space showed that the value between sleep and SB was the lowest (0.397) indicating high co-dependence between the two variables. MVPA had the highest values, suggesting low co-dependence with the other three behaviours.

Table 1. Comparison of characteristics of participants retained and not retained for analysis (n=1294), NDIT 1999–2012

| | Retained (n = 729) | Not retained (n = 565) |
|---|---|---|
| Age, y. mean (SD) | | |
| Cycle 21 | 20.3 (0.7) | 20.7 (0.9) |
| Cycle 22 | 24.0 (0.7) | 24.2 (0.8) |
| Female, % | 56.0 | 46.5 |
| Language other than French, % | 69.4 | 70.4 |
| Born in Canada, % | 93.6 | 90.1 |
| Mother university-educated, % | 42.9 | 21.6 |
| Highest education level attained*, % | | |
| High school | 20.6 | 41.6 |
| CEGEP/Technical school | 59.9 | 47.7 |
| University | 19.5 | 10.7 |
| Depressive symptoms, mean (SD) | | |
| Cycle 21 | 9.7 (7.8) | 9.7 (7.7) |
| Cycle 22 | 8.4 (7.8) | 8.7 (9) |
| MVPA (min/day), mean (SD) | 39.0 (54.3) | 43.0 (61.2) |
| Walking (min/day), mean (SD) | 33.3 (41.8) | 32.0 (42.2) |
| Sedentary behavior (min/day), mean (SD) | 413.6 (242.8) | 510.3 (421.5) |
| Sleep (min/day), mean (SD) | 501.1 (87.5) | 499.8 (135.4) |

CEGEP = Collège d'enseignement général et professionnel, MVPA = Moderate-to-Vigorous intensity Physical Activity; SB = Sedentary Behaviours; SD = Standard Deviation
* Highest education level attained is reported in NDIT cycle 21

Table 2. Compositional geometric mean and standard arithmetic mean of the percentage of time spent in sleep, sedentary behavior, walking and MVPA (n = 729), NDIT 1999-2012

| | Percentage of Time Spent in Each Behaviour | | | |
|---|---|---|---|---|
| | MVPA | Sedentary Behaviours | Sleep | Walking |
| Arithmetic Mean (SD) | 4.0 (4.1) | 39.5 (13.8) | 53.1 (12.7) | 3.4 (5.3) |
| Compositional Geometric Mean | 1.2 | 40.4 | 56.7 | 1.7 |

MVPA = Moderate to Vigorous Physical Activity, SD = Standard Deviation

When movement behaviours were considered together accounting for their multicollinearity using CoDA, the proportions of time spent in MVPA, walking, SB and sleep were not significantly associated with depressive symptoms at $p < 0.05$. None of the first ilr coordinates for time spent in MVPA ($\beta = -0.169$ ($\rho = 0.273$)), walking ($\beta = 0.034$ ($\rho = 0.861$)),

SB (β = 0.169 (ρ = 0.723)) or sleep (β = -0.034 (ρ = 0.948)) were statistically significantly associated with depressive symptoms (Table 3).

Table 3. Adjusted beta coefficients and 95% confidence intervals from log-ratio multiple regression models for the association between the proportion of time spent in sleep, SB, walking and MVPA and depressive symptoms (n = 729), NDIT (1999 –2012)

| First ilr coordinate for… | β (95% CI)* | SE | t value | p-value |
|---|---|---|---|---|
| MVPA | -0.169 (-0.472, 0.134) | 0.154 | -1.096 | 0.273 |
| Walking | 0.034 (-0.347, 0.415) | 0.194 | 0.175 | 0.861 |
| Sedentary behavior | 0.169 (-0.767, 1.106) | 0.477 | 0.355 | 0.723 |
| Sleep | -0.034 (-1.067, 0.998) | 0.526 | -0.065 | 0.948 |

CI = confidence interval, ilr = isometric log-ratio, MVPA = moderate-to-vigorous physical activity, SE = standard error
*Adjusted for age, sex, highest education level attained and depressive symptoms in cycle 21

Table 4 shows change in depressive symptoms with reallocation of 15 minutes between pairs of behaviours. Supplementary Table 3 Appendix F show the complete change in prediction matrices with changes in depressive symptoms with isotemporal reallocation of 10, 15, 20, 25 and 30 minutes. Reallocating 15 minutes from time spent walking, SB or sleep to MVPA was associated with decreases in depressive symptoms scores of -0.117, -0.093, and -0.089, respectively. Reallocating 15 minutes from time spent in MVPA to walking, SB or sleep resulted in increases in depressive symptoms scores of 0.280, 0.269 and 0.265, respectively. Similar increases were observed with reallocation of 10, 20, 25 and 30 minutes between pairs of behaviours (Supplementary Table 3 Appendix F).

Figure 6 shows percentage change in depressive symptoms from the base depressive symptoms score (9.04) with reallocation of time to and from MVPA. Reallocating time from walking to MVPA was associated with the highest percentage of decrease in depressive symptoms (e.g., reallocating 15 minutes from walking to MVPA was associated with a 1.3% decrease in depressive symptoms, compared to 1.0% with reallocation of 15 minutes from SB or sleep, respectively) (Figure 6). All changes were calculated from the base depressive symptoms score (i.e., prediction value (95% confidence level) = 9.04 (-4.25, 22.89), which was

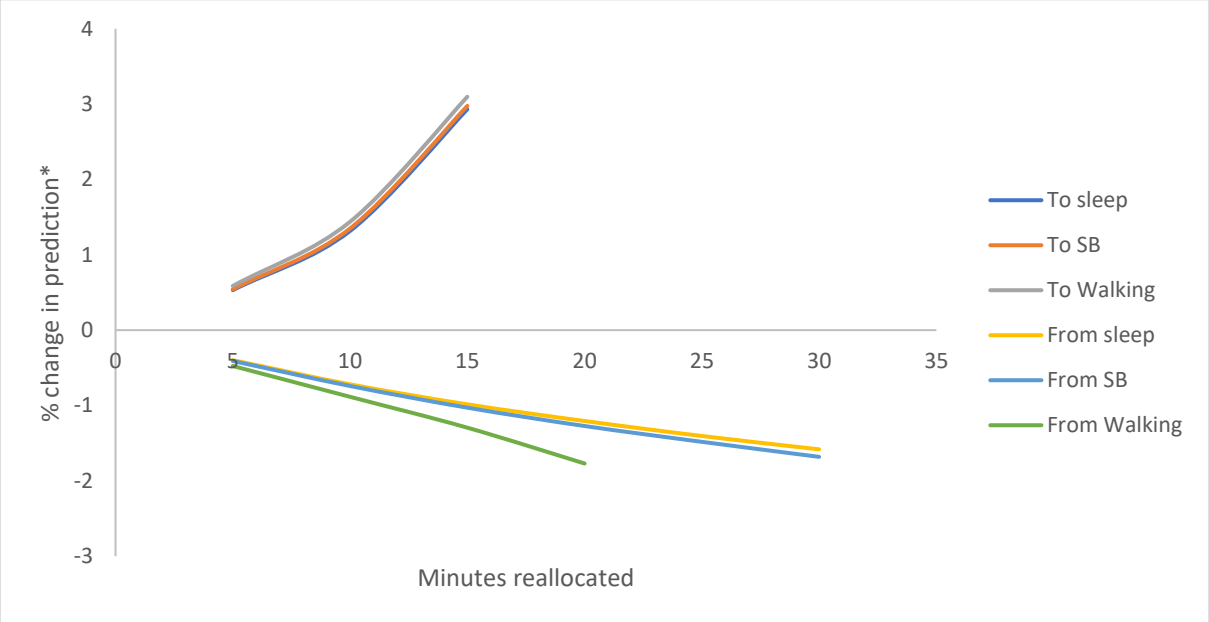
estimated using values at the compositional mean) and that percentages of change would differ if a different point inside the simplex space was considered.

Table 4. Change in prediction matrix showing changes in depressive symptoms with reallocation of 15 minutes from the behaviours in the columns to the behaviours in the rows (n=729), NDIT 1999–2012.

| Change in depressive symptoms with reallocation of 15 minutes……. | | | | |
|---|---|---|---|---|
| From…... | To……. | | | |
| | MVPA | Walking | SB | Sleep |
| MVPA | - | 0.280 | 0.269 | 0.265 |
| Walking | -0.117 | - | -0.024 | -0.029 |
| SB | -0.093 | 0.010 | - | -0.004 |
| Sleep | -0.089 | 0.015 | 0.004 | - |

MVPA = moderate-to-vigorous physical activity, SB = Sedentary Behaviours
Negative values indicate reduction in predicted depressive symptoms values with time reallocation, while positive values indicate an increase in predicted values with time reallocation

Figure 7. Predicted percentage change in depressive symptoms, from the base depressive symptoms value of 9.04 at the compositional mean, with reallocation of time from and to MVPA (n = 729), NDIT 1999–2012




MVPA = moderate to vigorous physical activity, SB = sedentary behaviours
*Change in depressive symptoms is expressed in percentages from the depressive symptoms score equal to 9.04 (prediction interval at 95% = (-4.25, 22.89)) , which was predicted at the compositional mean.

**Discussion**

Our aim in this study was to estimate the association between the proportion of time during a 24-hour period spent in each of MVPA, walking, SB and sleep and depressive symptoms in young adults. We hypothesized that time spent in these movement behaviors is associated with depressive symptoms in young adults. However, the log-ratio multiple regression models that account for multicollinearity across movement behaviours, did not detect any significant association.

Possible explanations for this finding are threefold. First, use of CoDA may have been contributory. Previous work in this realm assumed independence of time spent across movement behaviors and therefore examined their associations without taking multicollinearity into account. However, this assumption ignores the finite nature of time-use within a 24-hour period and the resultant multicollinearity across movement behaviors. Second, control of depressive symptoms in cycle 21 as a potential confounder could underpin the inability to detect an association. In our ilr multiple regression model, depressive symptoms in cycle 21 was the only variable significantly associated with depressive symptoms in cycle 22. Inclusion of depressive symptoms in cycle 21 may have explained most of the variation in the dependent variable in the model. Third, the 4-year follow-up in our study may have been contributory. Young adulthood is period of transitions in career and social life - it is possible there were important changes in movement behaviours during follow-up period and that this time-dependence in the exposure attenuated the association.

Our second objective was to estimate change in depressive symptoms with reallocation of time across pairs of movement behaviours. While CoDA accounts for multicollinearity across movement behaviours, ilr regression models do not assess whether a change in depressive symptoms relates to an increase in time spent in a behaviour in conjunction with the resultant decrease in time spent in other behaviours. The compositional isotemporal reallocation model quantifies the effect size of the association by computing the change in depressive symptoms with reallocation of specific amounts of time between two behaviours. Our reallocation model

suggested that declines in depressive symptoms were associated with reallocation of time from walking, SB or sleep to MVPA. Increases in depressive symptoms related to reallocation of time from MVPA to walking, SB or sleep. However, the estimates of change were uniformly small and mostly non-significant. This could relate to the fact that all estimates were derived from a single ilr model, which showed no significant association between movement behaviours and depressive symptoms. Additionally, the base depressive symptoms score estimated at the compositional mean had a wide prediction interval (i.e., mean (95% confidence level) = 9.04 (-4.25, 22.89)). Because of the wide prediction intervals, we suggest that our findings based on the compositional reallocation model need replication in future studies with larger sample sizes, before we can fully interpret the results.

Only two papers (del Pozo Cruz et al., 2020; Fairclough et al., 2020) are directly comparable to ours. Both used CoDA to examine accelerometer-measured movement behaviours in association with depressive symptoms. Using data collected from 3233 adults in the United States, Cruz et al. reported that only SB was significantly associated with depressive symptoms. Further, reallocating 60 minutes daily from SB to MVPA and sleep was associated with small reductions in depressive symptoms (del Pozo Cruz et al., 2020). However, their study was cross-sectional, although it did include adults with a wider age range (i.e., age 18 years or older) than in our study. Also, the authors did not report the significance of the association between MVPA, sleep or light intensity PA and depressive symptoms. Similar to our findings, Fairclough et al. reported that there was no significant association between MVPA, light intensity PA, SB or sleep and depressive symptoms among 359 children and adolescents in England. However, this study was also cross-sectional and the sample included adolescents age 9-13 years (Fairclough et al., 2020).

**Strengths**

This current analysis makes a unique contribution to the literature and has multiple strengths. Notably, the longitudinal study design in NDIT permitted correct alignment of study variables temporally, assuring that exposure preceded the outcome and that potential

confounders preceded the exposures. An important strength was use of CoDA, which permitted including all movement behaviours in the same model accounting for multicollinearity within a 24-hour period and controlling for potential confounders. The compositional isotemporal reallocation model provided, for the first time, estimates of changes in depressive symptoms with reallocation of specific amounts of time between behaviours.

**Limitations**

In NDIT, the only measure of light intensity PA was walking. Data were not obtained on other types of light intensity PA (e.g., yoga, golf, cooking, gardening). However an advantage of CoDA is that time-use data do not necessarily have to cover an exact 24-hour period (Chastin & Palarea-Albaladejo, 2015; Pedišić et al., 2017). As long as data are available for the same behaviours for all participants and are normalized to the same scale, the relative proportions of the behaviours investigated are maintained and incorporate all the information needed to conduct the analysis (Chastin & Palarea-Albaladejo, 2015). Nevertheless, considering all types of light intensity PA could have provided a more accurate measure of light intensity PA, which might have improved estimates of the association with depressive symptoms.

Generalizability of the findings may be limited because school selection was purposive (O'Loughlin et al., 2015). However, comparison of the characteristics of NDIT participants with those of participants in large provincial representative surveys suggests many similarities (Paradis et al., 2003). Loss-to-follow-up may have introduced selection bias and use of self-report data may have resulted in misclassification. Self-report data are generally subject to recall errors, selective answers errors and other biases. However, measuring time spent daily in different movement behaviours whether by accelerometer or self-reports is a challenge. While device-based measures improve precision, there are still challenges (i.e., classifying accelerometer data without postural allocation is less accurate in differentiating SB from light intensity PA and differentiating non-wear time from SB time remains a challenge and may lead to misclassification (Chastin, Granat, & posture, 2010; Hutto et al., 2013)). Difficulties in measuring movement behaviours are even more prominent in self-report data. Self-report

movement behaviours may be less accurate than accelerometry and depend primarily on participants' recall capacity and their estimates of time spent daily between PA, SB and sleep. Although a limitation, self-report remains a low-cost, valid method of measuring PA (Colley, Butler, Garriguet, Prince, & Roberts, 2019). We do however highlight the need for new self-report questionnaires that measure time spent in all movement behaviours and their subcomponents, while considering their compositional nature in a 24-hour period.

**Implications**

Currently, assessment of the efficacy of public health interventions relies primarily on randomised controlled trials, which are often expensive and challenging to implement in public health settings. While our time reallocation model is not a replacement for randomised controlled trials, it is a low-cost, reliable and relatively quick alternative "thought experiment" for obtaining estimates of change in depressive symptoms with reallocation of time between pairs of behaviours.

The Canadian movement behaviours guidelines for adults age 18−64 years included recommendations that stress the importance of balancing time spent daily in PA, SB and sleep to achieve optimal health (Ross et al., 2020), and highlight that the composition of movement behaviours is associated with all-cause mortality, adiposity and cardiometabolic biomarkers. There is currently no reference to depression or depressive symptoms. Supportive of previous work(Curtis et al., 2020; Fairclough et al., 2020; Larisch et al., 2020), our results suggest that there is no association between time-use in movement behaviors and depressive symptoms. That said, we acknowledge that our results need replication in other longitudinal studies before the findings can be translated into evidence-based recommendations. We therefore encourage replication of our findings in studies with larger sample sizes, objective measures and wider age ranges to better develop the evidence-base underpinning recommendations on public health interventions to prevent depression.

## Conclusion

This study is the first to examine the association between time spent daily in MVPA, walking, SB and sleep and depressive symptoms in a longitudinal study design in young adults. Time-use in movement behaviours was not associated with depressive symptoms, and reallocating time between movement behaviours resulted in minimal non-significant changes in depressive symptoms. Our findings need replication in longitudinal studies with larger sample sizes, wider age ranges and device-measured movement behaviours before considering the public health implications of the findings.

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## 5.3 Additional Results

### 5.3.1 Sensitivity Analysis

Two sensitivity analyses were conducted. The first was performed to ensure that there was no data distortion while imputing zero values in our compositional dataset. The second was to ensure that the control for depressive symptoms in cycle 21 did not influence the association between movement behaviours and depressive symptoms at cycle 22.

In the first sensitivity analysis, we imputed rounded zero values in our compositional dataset using multiplicative lognormal replacement. Specifically, we implemented a model-based multiplicative lognormal imputation of left-censored values. This technique imputes left-censored compositional values by the estimated geometric mean of the values below the corresponding limit of detection and applies a multiplicative adjustment to preserve the multivariate compositional properties of the samples (Palarea-Albaladejo et al., 2015a). We repeated the ilr multiple regression models after treating zero values using the lognormal multiplicative replacement method. An analysis of variance (ANOVA) for the regression models was conducted to compare the results of the models fitted after treating zeros using both the simple and the lognormal multiplicative replacement methods. The results of both analyses of variance are shown in Table 5 where it is clear that there is minimal difference between results obtained with both methods of zero replacement which ensures the consistency of our findings.

In the second sensitivity analysis, we examined the association between movement behaviours and depressive symptoms in cycle 22 with and without controlling for depressive symptoms in cycle 21 (i.e., to examine the possibility that our primary analysis controlled for a variable (i.e., depressive symptoms at cycle 21) on the causal pathway of the association of interest). An analysis of variance for the regression model was conducted to compare the results of ilr multiple regression models with and without controlling for depressive symptoms at cycle 21. The results of both analyses (shown in table 6) suggest that there is no association between movement behaviours and depressive symptoms at cycle 22.

Table 5. Comparison of the analysis of variance (ANOVA) for ilr multiple regression models fitted after imputing zeros in the dataset using two different zero replacement methods (n = 729), NDIT 1999-2012

| | ANOVA for regression for models fitted after zero values treatment using | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Simple multiplicative replacement | | | | Lognormal multiplicative replacement | | | |
| | Sum sq | df | F value | Pr(>F) | Sum sq | df | F value | Pr(>F) |
| Ilr coordinates for MVPA, Walking, SB, Sleep | 63 | 3 | 0.441 | 0.724 | 61 | 3 | 0.429 | 0.732 |
| Age | 38 | 1 | 0.795 | 0.373 | 38 | 1 | 0.794 | 0.373 |
| Sex | 54 | 1 | 1.147 | 0.285 | 55 | 1 | 1.160 | 0.282 |
| Highest education level attained | 165 | 2 | 1.748 | 0.175 | 165 | 2 | 1.748 | 0.175 |
| Depressive symptoms | 8967 | 1 | 189.567 | **<0.001** | 8969 | 1 | 189.608 | **<0.001** |

ANOVA = Analysis of Variance, df = Degrees of Freedom, MVPA = Moderate to Vigorous Physical Activity, SB = Sedentary Behaviours, sum sq = Sum of Squares
Bold implies statistically significant associations ($p < 0.05$)

Table 6. Comparison of the analysis of variance (ANOVA) for ilr multiple regression models fitted with and without controlling for depressive symptoms in cycle 21 (n = 729), NDIT 1999-2012

| | ANOVA for regression for models fitted with and without controlling for depressive symptoms at cycle 21 | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Controlling for depressive symptoms at cycle 21 | | | | Without controlling for depressive symptoms at cycle 21 | | | |
| | Sum sq | df | F value | Pr(>F) | Sum sq | df | F value | Pr(>F) |
| Ilr coordinates for MVPA, Walking, SB, Sleep | 63 | 3 | 0.441 | 0.724 | 330 | 3 | 1.843 | 0.138 |
| Age | 38 | 1 | 0.795 | 0.373 | 51 | 1 | 0.854 | 0.356 |
| Sex | 54 | 1 | 1.147 | 0.285 | 615 | 1 | 10.310 | **0.001** |
| Highest education level attained | 165 | 2 | 1.748 | 0.175 | 87 | 2 | 0.726 | 0.484 |
| Depressive symptoms | 8967 | 1 | 189.567 | **<0.001** | | | | |

ANOVA = Analysis of Variance, df = Degrees of Freedom, MVPA = Moderate to Vigorous Physical Activity, SB = Sedentary Behaviours, sum sq = Sum of Squares
Bold implies statistically significant associations ($p < 0.05$)

# Chapter 6: Discussion

## 6.1 Overview of thesis

The objectives of this thesis were to estimate the association between time spent daily in MVPA, walking, SB and sleep and depressive symptoms in young adults and to estimate change in depressive symptoms after reallocating time spent across pairs of movement behaviours. These objectives were examined in a longitudinal study design which followed young adults over four years from age 20 to 24. We used CoDA to examine time-use in MVPA, walking, SB and sleep and their association with depressive symptoms. We also used a compositional isotemporal reallocation model to estimate change in depressive symptoms with reallocation of time between pairs of movement behaviours. CoDA is an established analytical method that has recently been applied to time-use epidemiology. It has been gaining momentum in health research since Chastin et al. introduced it in 2015 to examine the association between movement behaviours and obesity and cardiometabolic health markers among adults (Chastin et al., 2015). CoDA represents a promising step forward in research investigating movement behaviours as modifiable risk factors for depressive symptoms.

This thesis discussion summarizes our findings, compares our results with the existing literature and provides insight into reasons underpinning similarities and differences. The discussion also presents study strengths and limitations. Finally, we conclude by discussing the implications of the results in regard to public health and to future research on depressive symptoms in young adults.

## 6.2 Comparison of Findings with the Literature

### 6.2.1 Time-use in PA, SB and Sleep and Depressive Symptoms

We examined the association between time spent in a 24-hour period in MVPA, walking, SB and sleep, and depressive symptoms using data collected in a longitudinal study design and ilr multiple regression models. Our hypothesis was that the proportion of time spent in these movement behaviors is associated with depressive symptoms. However, our models, which took multicollinearity between movement behaviours into account and controlled for potential confounders, did not detect a significant association between the exposure and depressive symptoms. To compare our findings with the literature, we differentiate two categories of studies; non-compositional analysis studies that examine movement behaviours in isolation with depressive symptoms, and compositional analysis studies that include all movement behaviour and account for their multicollinearity in association with depressive symptoms. We also discuss possible explanations for our findings including reasons for differences observed with the extant literature.

First, we compare our results with studies that examined the association between each movement behaviour separately and depressive symptoms. There are inherent differences between studies that used compositional analysis of movement behaviours and those that did not, including the number of movement behaviours included in analysis and the accounting for the co-dependence between the behaviours. However, studies that used non-compositional analysis comprise a large part of this literature and it is important to consider how the findings from these studies contribute to our understanding of the association between movement behaviours and depressive symptoms. While we found no significant association between movement behaviors and depressive symptoms, studies that used non-compositional analysis report mixed results. A recent systematic review reported mixed results in regard to the relationship between objectively measured PA and depressive symptoms in youth (Poitras et al., 2016). Of the four cross-sectional studies included in the review, one reported a positive association between PA and depressive symptoms (Wiles et al., 2012), two studies that found no association (Johnson et al., 2008; Toseeb et al., 2014) and one study reported mixed results

(Young et al., 2014). Aligned with our results, the longitudinal study in the review found no association between MVPA and depressed mood or depressive symptoms after three years of follow up (Toseeb et al., 2014). In a recent meta-analysis examining the association between SB and depressive symptoms, ten studies reported a significant association and 14 studies found no association (Zhai et al., 2015). For sleep, 11 studies in a systematic review by Chaput et al. reported a significant association between sleep duration and depressive symptoms, and three studies reported no significant association (Chaput et al., 2016).

One possible explanation for differences between previous studies and our findings is our use of CoDA, which accounted for multicollinearity across movement behaviours. Previous studies assumed independence in time spent across movement behaviors and therefore examined their associations with depressive symptoms in isolation or together, but without taking multicollinearity into account. The assumption of independence ignores the finite nature of time-use within a 24-hour period and the co-dependence of time spent across movement behaviors. In our study, it is possible that the lack of association between movement behaviours and depressive symptoms related to use of CoDA. An alternate explanation is that we controlled for depressive symptoms in cycle 21, which was the only covariable significantly associated with depressive symptoms in cycle 22. Most studies to date do not control for earlier depressive symptoms, despite its bidirectional association with PA, SB and sleep (Fang, Tu, Sheng, Shao, & medicine, 2019; Pereira, Geoffroy, & Power, 2014; Raudsepp, 2016). This bidirectional association means that earlier depressive symptoms can influence levels of movement behaviours, which in turn may influence later depressive symptoms outcomes. Controlling for earlier depressive symptoms in our study, may have attenuated the estimate of the association between movement behaviours and later depressive symptoms. A third possible explanation for our null findings could be the duration of follow-up in our study. Longitudinal follow-up is critical to establish the temporality between variables that is needed to support causal inference. However, initially measured variables could change substantially during long follow-up periods. Important transitions in career and social life could have occurred during the 4-year follow-up period in NDIT (between age 20 and 24), which could have resulted in important changes in all study variables and in turn, attenuated the estimates.

Second, we compared our results with four previous studies that all used CoDA to investigate all movement behaviours in the same analysis in association with depressive symptoms (Curtis et al., 2020; del Pozo Cruz et al., 2020; Fairclough et al., 2020; Larisch et al., 2020). Larisch et al. examined 349 office workers in Sweden. Curtis et al. studied 430 adults ages 18-65 in Australia. Cruz et al. studied 3233 adults ages 18 or older in the US, and Fairclough et al. examined 359 ages 9-13 in England. However, unlike NDIT, all four studies were cross-sectional, all used accelerometer-measured movement behaviours and their samples comprised children and adolescents (Fairclough et al., 2020) or adults with a wider age range (Curtis et al., 2020; del Pozo Cruz et al., 2020; Larisch et al., 2020) than in NDIT. Despite differences, three of the four studies reported results aligned with our findings of no significant association (Curtis et al., 2020; Fairclough et al., 2020; Larisch et al., 2020). Only one study reported a significant association, and that was restricted to the association between the proportion of time spent in SB and depressive symptoms (without mention of other movement behaviours proportions) (del Pozo Cruz et al., 2020). We initially considered the possibility that this difference is related to differences in the proportion of time spent daily in SB relative to other behaviours; however, the proportions were similar (40.4% vs 40.47%). We also considered that our longitudinal study design, the use of self-report movement behaviours or the inclusion of walking as the only light intensity PA may be relevant. However, similar differences exist with the other three studies that reported results similar to ours. The only factor that differed between the Cruz et al. study and the other studies was the demographic make-up of the sample. One-quarter (23%) of their sample was age 65 years or older, and 39% of participants had at least one chronic disease. Older age and chronic disease are associated with higher levels of depression (Huang, Dong, Lu, Yue, & Liu, 2010), which might have influenced the association between SB and depressive symptoms.

### 6.2.2 Change in Depressive Symptoms with Reallocation of Time Between Movement Behaviours

Our second objective was to estimate change in depressive symptoms with reallocation of time between pairs of movement behaviours. While ilr multiple regression models examine

the association between time spent daily in movement behaviour and depressive symptoms, they do not assess whether a change in depressive symptoms relates to an increase in time spent in a behaviour or the resultant decrease in time spent in other behaviours. Our compositional isotemporal reallocation model indicated that there was a decrease in depressive symptoms with time reallocation from walking, SB or sleep to MVPA. Further, there was an increase in depressive symptoms with time reallocation from MVPA to walking, SB, or sleep. However, the estimates of change were uniformly small and mostly non-significant. This could relate to the fact that all estimates were derived from a single ilr model which showed no significant association between movement behaviours and depressive symptoms. Additionally, the base depressive symptoms score estimated at the compositional mean, had a wide prediction interval (i.e., 95% confidence level (score = 9.04 (-4.25, 22.89)). Further, the effect of PA activity on depressive symptoms is weaker in non-clinical populations (Rebar et al., 2015). Thus, it is possible that our sample of relatively healthy young adults (i.e., average depressive symptoms score (SD) = 8.4 (7.8)) underpins the minimal non-significant changes in depressive symptoms with time reallocation between movement behaviours.

The study by Cruz et al. (del Pozo Cruz et al., 2020) is unique in that it is the only study in literature to date that used a compositional isotemporal reallocation model to quantify change in depressive symptoms. The authors reported that replacing 60 minutes of SB with MVPA (but not light intensity PA) was associated with a significant reduction in depressive symptoms in adults (del Pozo Cruz et al., 2020). Although theoretically interesting, attaining 60 minutes of MVPA daily may not be achievable in many people. In addition, 60 minutes of MVPA daily totals 420 minutes weekly, which is almost three times the recommended amount of MVPA weekly for adults (Ross et al., 2020).

## 6.3 Study Strengths

### 6.3.1 NDIT

This thesis comprises a secondary analysis of data drawn from the 20-year longitudinal NDIT study, in which 858 young adults participated in cycle 22. The NDIT dataset comprises data on a wide range of variables and therefore provided an ideal infrastructure to attain our study objectives. Additionally, the NDIT study design permitted correct alignment across variables temporally, assuring that exposure preceded the outcome and that potential confounders preceded the exposure. Overall, our analysis permits addressing gaps in the extant literature and offers new insight into the association between movement behaviours and depressive symptoms in young adults.

### 6.3.2 Longitudinal design

A strength of our study is its longitudinal design. Previous studies that used CoDA to examine all movement behaviours in association with depressive symptoms were cross-sectional (Curtis et al., 2020; del Pozo Cruz et al., 2020; Fairclough et al., 2020; Larisch et al., 2020). Our study is the first to examine this association in a longitudinal design over a 4-year period of follow-up during young adulthood. This longitudinal design has many advantages over cross-sectional studies including that the design helped establish the ideal temporal ordering of variables in which our covariables (i.e., age, sex, highest educational level attained, depressive symptoms in cycle 21) preceded the exposure variables (i.e., time spent daily in MVPA, walking, SB, sleep) which in turn, preceded the outcome variable (i.e., depressive symptoms in cycle 22). The correct temporal sequence and follow-up over 4-year period are important features of the study design in terms enabling causal inference, as per Hill's criteria (Hill, 1965). In addition, the longitudinal design contributes to reduction in possible misclassification in the study variables due to recall bias.

### 6.3.3 An innovative technique: CoDA

A primary strength of our study is use of innovative CoDA techniques, which allowed us to account for co-dependence within a 24-hour period in time spent in four movement behaviours. Previous studies examined movement behaviours in isolation or without accounting for co-dependence. While these studies contribute to our understanding of the association between movement behaviours and depressive symptoms, CoDA allowed us to add new insight into the association with more accurate statistical estimates. In addition, CoDA permitted application of compositional isotemporal reallocation modeling, which has potential to inform public health interventions about possible changes in depressive symptoms with reallocation of time between movement behaviours. Previous studies provided findings about the benefits of increasing or decreasing single movement behaviours on depressive symptoms. This contrasts with the CoDA and compositional isotemporal reallocation models which incorporate the new concept of time composition within the 24-hour period. This may better position public health intervention to attain movement guidelines by encouraging individuals to increase time spent daily in one behaviour while decreasing time in other behaviours.

## 6.4 Limitations

### 6.4.1 Self-Report Questionnaires

NDIT data were collected in self-report questionnaires which are subject to recall errors, selective answer errors and other biases. Limitations of self-report are particularly salient in terms of measuring time spent in movement behaviours, which are generally difficult to measure for multiple reasons. For example, PA is often measured in bouts of minutes per day, while SB is measured in hours per day on weekday- and weekend-days, and sleep is measured using go-to-sleep and wake-up times. Different reference periods and response options across movement behaviors may confuse participants and introduce inaccuracy into estimates of movement behaviours within a 24-hour period. Additionally, time-use in movement behaviours is dependent on the ability of the participant to recall accurately and may be subject to misclassification arising from selective answers that tend to overestimate socially acceptable

behaviours such as PA at the expense of behaviours such as SB (Schmidt, Blum, Valkanover, Conzelmann, & exercise, 2015; Sonstroem, Morgan, Sports, & Exercise, 1989). Finally, although device-based measures of movement behaviours may provide more accurate data than self-report, use of objective measures is also challenged. Accelerometer data without postural allocation is less accurate in differentiating SB and light intensity PA (Chastin et al., 2010) and it can be difficult to differentiate between non-wear and SB times (Hutto et al., 2013) which may lead to misclassification. Thus, while we acknowledge the limitation of self-report data, this method remains a low-cost valid method of measuring PA. SB and sleep (Colley et al., 2019).

Another limitation indirectly related self-reports is our inclusion of walking as the only light intensity PA in our analysis. This is because walking is the only light intensity PA behaviour that was measured in NDIT cycle 21 (i.e., other light intensity PA such as yoga, golf, cooking and gardening were not measured in cycle 21). Without measures of other light intensity PA behaviours, we were missing data on the full 24-hour spectrum of movement behaviors. However, an advantage of CoDA is that it can be applied to time-use data of all durations, and not necessarily to an exact 24-hour period (Chastin & Palarea-Albaladejo, 2015; Pedišić et al., 2017). Thus, as long as data are available for the same behaviours for all participants and the data are normalized to the same scale, the relative proportions of the behaviours investigated are maintained and incorporate all the information needed to conduct the analysis (Chastin & Palarea-Albaladejo, 2015). However, we acknowledge that considering all types of light intensity PA would have provided a more comprehensive measure of light intensity PA, which might have increased the accuracy of the estimates of the association with depressive symptoms.

### 6.4.2 Generalisability of results

At inception, the NDIT sample of schools was purposively selected to obtain a sample of adolescents that included those that spoke French or English, those living in urban, suburban and rural neighborhoods and those if high, moderate and low socioeconomic status. Comparison of the characteristics of NDIT participants with those of participants in large provincially

representative surveys, suggests many similarities (Paradis et al., 2003) so that the findings may be generalizable to groups with similar characteristics. Because the NDIT sample was primarily white, the findings may not be generalizable to young adults with other backgrounds.

### 6.4.3 Possible biases

While the longitudinal study design is a strength, loss-to-follow-up and missing data in NDIT between cycle 21 and 22 may have introduced selection bias into the results. Our analytical sample comprised the 729 participants with data available in both cycle 21 and 22, which represents 82% of NDIT participants at cycle 21 (n = 880). While the retention rate was high, participants lost-to-follow-up as well as those excluded for missing data (n = 151) represent 17% of the total sample at cycle 21. Those 151 participants were excluded for various reasons (i.e., loss-to follow-up (n = 22), not participating in cycle 21 (n = 62), missing data for one or more variables (n = 50), discrepant or aberrant data (n = 17). Selection bias occurs if exclusion of participants results in a biased estimate of the association (i.e., if the association between exposure and outcome in the study population (those retained) differs from the association among those lost to follow-up). Because we cannot measure the association in those lost to follow-up between cycle 21 and 22 (n = 151), we cannot ascertain with certainty whether there is selection bias. However, we do note in Supplementary Table 4 in Appendix F that those not retained resemble those retained on numerous indictors (note that the values of several of the variables studied in Table 4 were drawn from cycle 1). However, while the distribution of key variables appears to be similar in the two groups, we cannot conclude without in-depth analyses beyond the scope of this MSc thesis that there is no selection bias.

Another limitation is the length of the follow-up period during young adulthood. Young adulthood is a period of important transitions in career and social life, with possibly major shifts in movement behaviours. There may have been notable shifts in the proportion of time spent in different movement behaviours during the 4 years of follow-up period, which might have introduced misclassification bias in the estimates.

Residual confounding may be an issue. In our study, we constructed three DAGs, one for the association between each of PA, SB and sleep, and depressive symptoms, with the aim of selecting potential confounders of the association of interest. After examining the DAGs, we decided to control for age, sex, highest educational level attained and depressive symptoms at cycle 21 as potential confounders of the association between movement behaviours and depressive symptoms in cycle 22. However, other factors such as ethnicity and family structure were not controlled for a variety of reasons. For example, approximately 78.3% of our analytical sample were white, so we did not control for ethnicity. Additionally, we did not collect data on current family structure, so we were unable to control for it. It is possible that not taking these and other factors into account resulted in residual confounding, which might have affected the estimate.

Finally, we controlled for depressive symptoms as a potential confounder of the association between movement behaviours and later depressive symptoms. However, there was overlap in the time reference period for the measurement of depressive symptoms at cycle 21 (i.e., measured over the past 14 days) and the time of measurement of PA, SB and sleep which were measured over the past 7 days, a day in general, and the past month, respectively. As such, our analysis might have controlled for a variable (i.e., depressive symptoms in cycle 21) which is on the causal pathway between movement behaviours and later depressive symptoms in cycle 22. We conducted a sensitivity analysis for the association with and without controlling for depressive symptoms in cycle 21 and both analyses (shown in Table 6) suggest no association. Additionally, PA, SB and sleep were measured over different periods. We assumed that each measure reflected a recent estimate of the average amount of time spent in each behaviour daily and that their sum reflects time spent in these behaviours over a 24-hour period.

## 6.3 Implications

We encourage replication of this work in larger studies in a variety of settings and age groups to confirm the findings before considering their implications for public health. CoDA and isotemporal reallocation modeling are robust methods for dealing with data that are part of a whole. They are easily applicable to a wide range of readily available data from multiple epidemiological studies. Application of CoDA can provide new insights on how the proportion of time spent in various behaviours daily are associated with different physical or mental health outcomes. Currently, there are 24-hour movement behaviour guidelines that inform public health about the optimal distribution of time daily in PA, SB and sleep. The time reallocation model provides information on change in health outcomes with the reallocation of specific amounts of time between behaviours. Until recently, this has been difficult to estimate without randomised controlled trials, which tend to be expensive and complex to implement. While time reallocation modeling is not a replacement for randomised control trials, it is a low-cost reliable method of obtaining estimates of change in health outcomes with change in movement behaviours. These estimates can contribute to more effective public health interventions in the future.

The Canadian movement behaviour guidelines for adults age 18-64 years underscore the importance of balancing time spent daily in PA, SB and sleep to achieve optimal health (Ross et al., 2020), and suggest that adherence to the guidelines is associated with all-cause mortality, adiposity and cardiometabolic biomarkers. However, the guidelines did not include information on depression or depressive symptoms. Our results suggest that if movement behaviours have any effect on depressive symptoms in young adults, it is mostly a small effect (del Pozo Cruz et al., 2020; Yasunaga, Shibata, Ishii, Koohsari, & Oka, 2018). However, we acknowledge that our findings need replication in other studies, possibly using device-measured movement behaviours, before translating the results into recommendations.

## 6.4 Future Directions

As indicated above, our findings need to be replicated in longitudinal studies using device-measured PA, SB and sleep. We encourage use of CoDA techniques in the analyses. To help future researchers replicate our work, we developed a list of the most important analytic challenges encountered and the decisions taken to deal with these challenges. The checklist can serve a guide to facilitate using CoDA. Some changes to the techniques used in our study can be applied in future studies. For example, improvement in compositional isotemporal reallocation modeling might be achieved by reallocating time from a behaviour to multiple other behaviours while maintaining the total sum constant. This technique may be more realistic in clinical settings where it may be more achievable to replace time spent in a behaviour with similar time in multiple other behaviours. Additionally, future studies may consider conducting the isotemporal reallocation model starting from points other than the compositional geometric mean. These could represent different profiles of movement behaviour distributions within a 24-hour period, which better reflect high proportions of time spent in a specific behaviour relative to other behaviours. Conducting the time reallocation model at these points may provide better understanding of the association between daily movement compositions with very high proportions of time spent in a single behaviour and depressive symptoms, especially for behaviours such as sleep which has a U-shaped association with depressive symptoms (Kaneita et al., 2006).

Introduction of CoDA to time-use epidemiology by Chastin et al. in 2015 (Chastin et al., 2015) and publication of the world's first movement guidelines for children and youth in 2016 (Tremblay et al., 2016) have contributed to growing interest in studying movement behaviours and their association with health outcomes. Many studies use accelerometers for more accurate measurement of movement behaviours. However, device-based measurement of movement behaviours is expensive and has its own flaws (de Almeida Mendes et al., 2018). We are the first to employ self-report movement behaviours in CoDA analysis. Self-report movement behaviours provide valuable information in large samples. However, new self-report questionnaires need to be developed, that measure time spent in all movement behaviours and

their subcomponents that consider their compositional nature within the 24-hour period. Such self-report questionnaires may represent considerable improvement over currently available questionnaires, if they provide more accurate measures of movement behaviours. In addition, future research could benefit from a personal behaviours measurement technique called Ecological momentary assessment (EMA). EMA, in the form of repeated self-reports that measure movement behaviours in real time, may represent an improvement over self-reports since it could help minimize recall bias.

# Chapter 7: Conclusion

In this thesis, we estimated time spent in movement behaviours as proportions that sum to 100 in a 24-hour period. We investigated whether these proportions are associated with depressive symptoms in young adults in a longitudinal study design. The proportions of time spent in movement behaviours were not significantly associated with depressive symptoms. We then estimated how reallocating time from one behaviour to another contributed to change in depressive symptoms using a compositional isotemporal reallocation model. The model showed that reallocating time from MVPA to walking, SB or sleep resulted in an increase in depressive symptoms and reallocating from walking, SB or sleep to MVPA resulted in a decrease in depressive symptoms. However, the estimates were minimal and mostly non-significant.

Despite null findings, our study provides new insight on whether considering all movement behaviours together may be associated depressive symptoms in young adults. We encourage future researchers to continue investigating the effect of movement behaviours on depressive symptoms, using CoDA. It is likely important that researchers and practitioners to consider movement behaviours over a 24-hour period as a composition of PA, SB and sleep proportions, rather than as isolated behaviours. Replication of our findings is needed before translating the findings into public health recommendations.

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# Appendices

## Appendix A: Items in NDIT Questionnaires Used to Measure Study Variables

**84. In the past two weeks, how much of the time have you…?**

| | At no time | Some of the time | Slightly less that half of the time | Slightly more than half of the time | Most of the time | All the time |
|---|---|---|---|---|---|---|
| Felt low in spirits or sad | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |
| Lost interest in, or could no longer enjoy your daily activities | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |
| Felt lacking in energy and strength | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |
| Felt less self-confident | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |
| Had a bad conscience or feelings of guilt | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |
| Felt that life wasn't worth living | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |
| Had difficulty concentrating (when reading the newspaper or watching TV) | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |
| Felt very restless | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |
| Felt subdued or slowed down | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |
| Had trouble sleeping at night or waking up too early | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |
| Suffered from reduced appetite | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |
| Suffered from increased appetite | ☐ | ☐ | ☐ | ☐ | ☐ | ☐ |

Figure 8. Major Depression Inventory (MDI), NDIT Cycles 21 and 22

**54. During the last 7 days, on how many days did you do vigorous physical activities (heavy lifting, digging, aerobics, fast bicycling) for at least 10 minutes at a time?**

0☐ None → **Go to question 56**

_____Days in the last 7 days

**55. On the days that you did vigorous physical activities, how many minutes did you usually do per day?**

_____minutes per day

**56. In the last 7 days, on how many days did you do moderate physical activities (carrying light loads, bicycling at a regular pace, doubles tennis) for at least 10 minutes? Do not include walking.**

0☐ None → **Go to question 58**

_____Days in the last 7 days

**57. On the days that you did moderate physical activities, how many minutes did you usually do per day?**

_____minutes per day

**58. In the last 7 days, on how many days did you walk for at least 10 minutes at a time?**

0☐ None → **Go to question 60**

_____Days in the last 7 days

**59. On the days that you walked, how many minutes did you usually spend walking per day?**

_____minutes per day

Figure 9. International Physical Activity Questionnaire (IPAQ-SF), NDIT Cycle 21

**60. How many hours of television (including video movies) do you usually watch in a single day? Write "0" if none. Write "LT ½" if less than ½ hour.**

On weekdays, I usually watch _____hour(s) of television a day

On weekends, I usually watch _____ hour(s) of television a day

**61. How many hours do you usually spend on a computer in a single day for school or at work? Write "0" if none. Write "LT ½" if less than ½ hour.**

On weekdays, I usually use the computer _____ hour(s) a day for work or school

On weekends, I usually use the computer _____ hour(s) a day for work or school

**62. How many hours do you usually spend on a computer in a single day during your leisure time (playing computer games, using the Internet)? Write "0" if none. Write "LT ½" if less than ½ hour.**

On weekdays, I usually use the computer _____ hour(s) a day in my leisure time

On weekends, I usually use the computer _____ hour(s) a day in my leisure time

**63. In a typical week, how much time did you usually spend reading (books, magazines, newspapers, homework)? Write "0" if none. Write "LT ½" if less than ½ hour.**

On weekdays, I usually read _____ hour(s) a day

On weekends, I usually read _____ hour(s) a day

Figure 10. Sedentary Behaviours, NDIT Cycle 21

**69. In the past month, at what time did you usually go to sleep at night?**

_____ in the evening

**70. In the past month, at what time did you usually wake up in the morning?**

_____in the morning

Figure 11. Go-to-sleep and Wake up times, NDIT Cycle 21

# Appendix B: Directed Acyclic Graphs (DAGs)

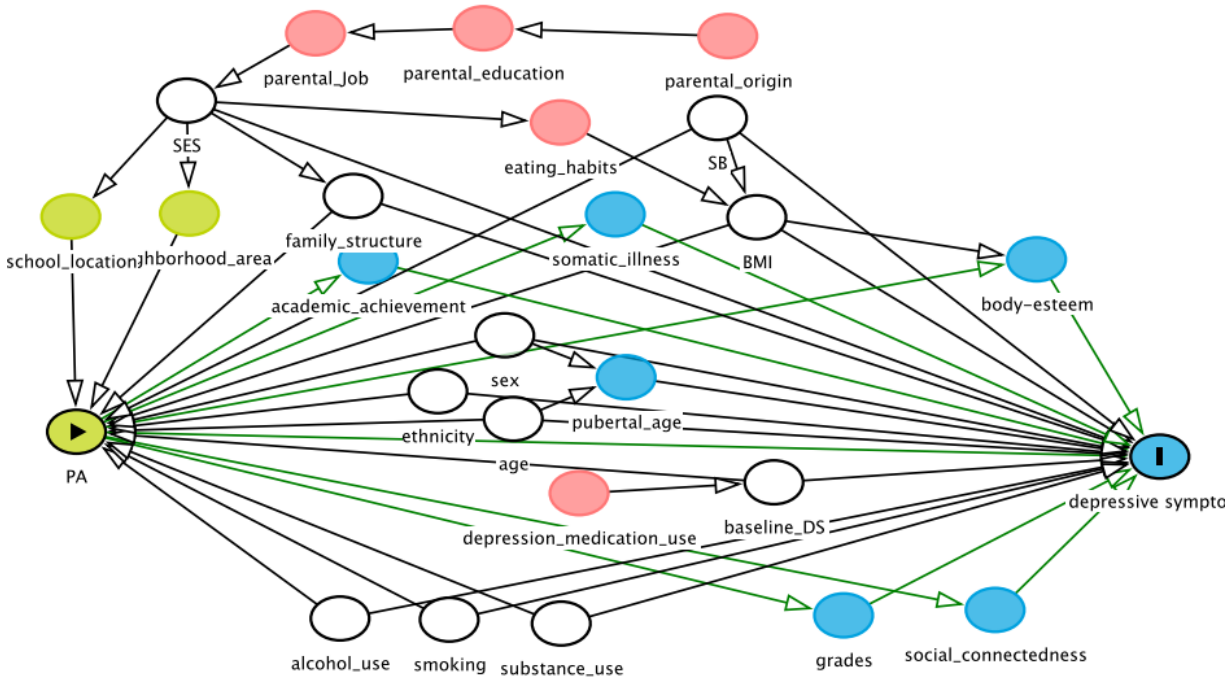


Figure 12. Directed Acyclic Graph showing the possible confounders in the association between physical activity and depressive symptoms.

Green: exposure or ancestor of exposure; Blue: outcome or ancestor of outcome; Red: ancestors of both exposure and outcome (confounder); white: adjusted variable; Green line: causal path.

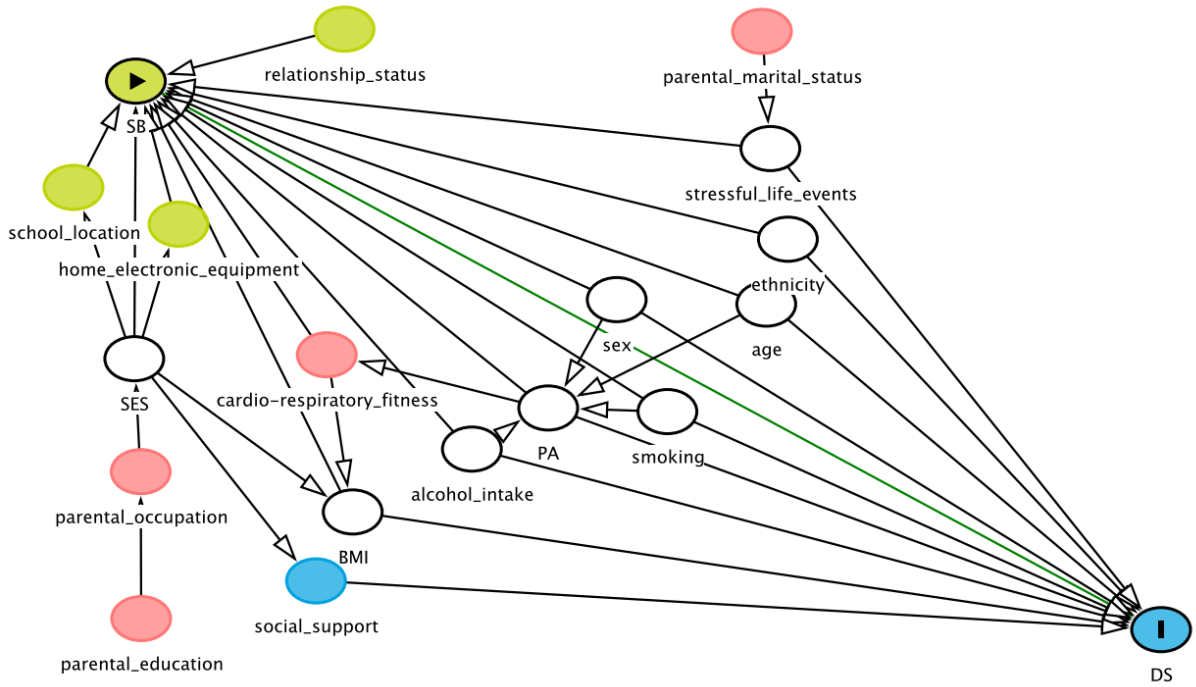


Figure 13. Directed Acyclic Graph showing possible confounders of the association between sedentary behaviours and depressive symptoms.

Green: exposure or ancestor of exposure; Blue: outcome or ancestor of outcome; Red: ancestors of both exposure and outcome (confounder); white: adjusted variable; Green line: causal path.

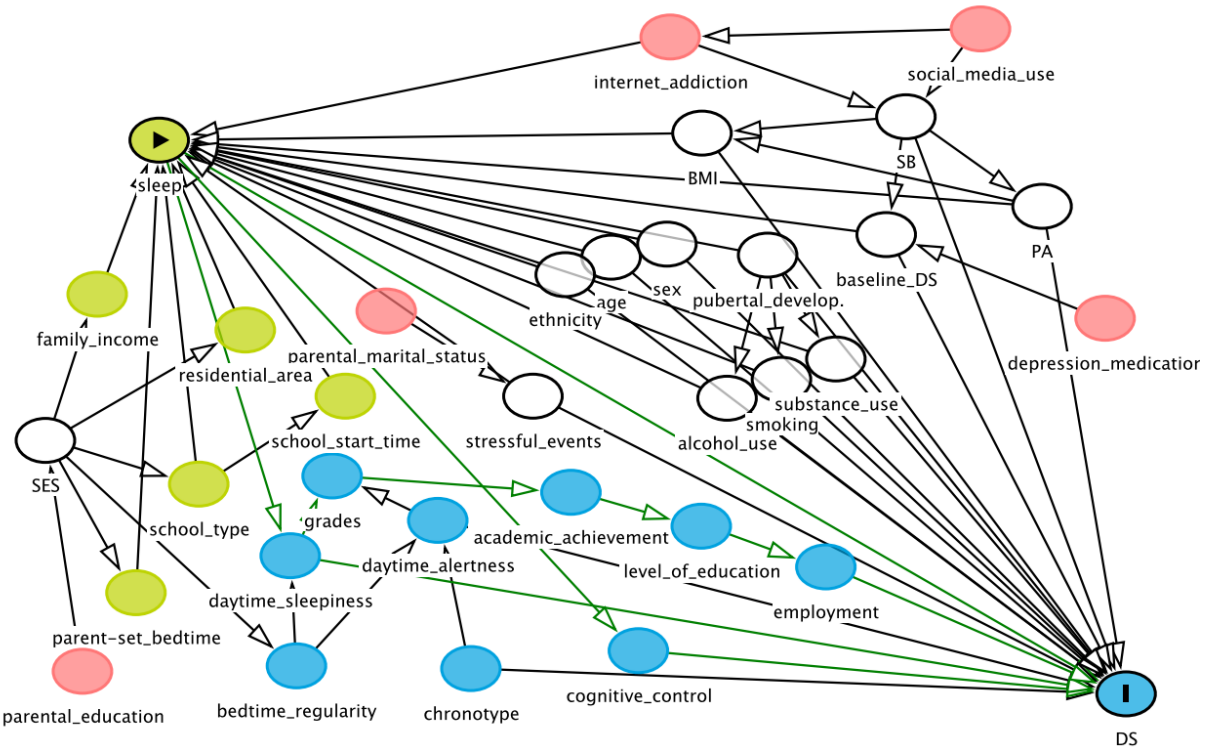


Figure 14. Directed Acyclic Graph showing possible confounders of the association between sleep and depressive symptoms.

Green: exposure or ancestor of exposure; Blue: outcome or ancestor of outcome; Red: ancestors of both exposure and outcome (confounder); white: adjusted variable; Green line: causal path.

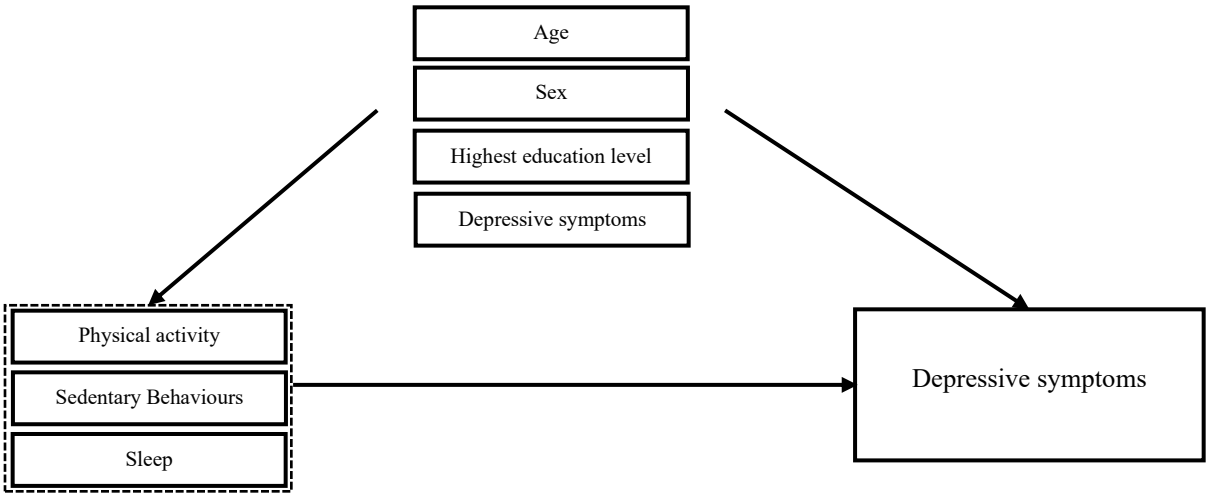


Figure 15. Directed Acyclic Graph illustrating potential confounders of the association between physical activity, sedentary behaviours and sleep as exposure variables, and depressive symptoms as the outcome variable.

# Appendix C: NDIT Consent Form Used at Study Inception in 1999-2000, and Original Ethics Approval Documents

RÉGIE RÉGIONALE
DE LA SANTÉ ET DES
SERVICES SOCIAUX
**DE MONTRÉAL-CENTRE**

November 18, 1999

**MCGILL UNIVERSITY STUDY ON NICOTINE DEPENDENCE IN TEENS**

Investigators: J. O'Loughlin, PhD., G. Paradis, MD, P. Clarke, PhD., J. Hanley, PhD, R. Tyndale, PhD., J. DiFranza, MD

Dear Parent/Guardian:

The Public Health Directorate of Montréal-Centre in collaboration with McGill University, and the Universities of Toronto and Massachusetts, is undertaking a 3-year study among Secondary I students in 12-15 Montreal high schools to study how smoking becomes an established habit in certain adolescents. All Secondary I students in your child's school have been asked to participate because we need to study children who smoke, as well as children who do not smoke. The ultimate purpose of this research is to help us develop more effective strategies to prevent the onset of smoking in children, as well as to help youth who want to quit smoking. In addition, this study will examine the relationship between smoking, weight, and blood pressure during adolescence. The study has 2 parts:

**Part I** - In the next few weeks, our research team will visit your child's classroom. Two interviewers will administer a 45-minute in-class questionnaire to all students about their smoking experiences. The interviewers will visit your child's class again 3-4 months later and every 3-4 months after that for the next 3 years (in Secondary I, II and III) to re-administer the questionnaire in order to collect updated information on the students' smoking experiences. Trained technicians will measure your child's height, weight, skinfold thickness, waist circumference and blood pressure once a year. All data will be stored in locked storage areas at the Public Health Directorate.

**Part II** - An important aspect of this study is to investigate if genetic factors are involved in smoking uptake. To explore this possibility, we will collect a blood sample from each student for genetic analysis. During data collection in March 2002, a nurse will draw 10 ml of blood (2 teaspoons) for genetic analysis. The samples will be analyzed and stored at the University of Toronto, which specializes in this type of genetic analysis. The blood samples will be labeled only by number and the results of the genetic test will remain completely confidential. A master list linking the child and the identification number will be stored securely at the Public Health Directorate. Only the principal investigator and the project coordinator will have access to the list. This list will be destroyed at the end of the study. It will be impossible to provide any individual results of the genetic testing to anyone because they will never be linked to a particular name. After the list is destroyed, all blood samples will be completely anonymous. The samples will be stored for a maximum of ten (10) years for future genetic analysis exclusively related to smoking.

**Request for your consent** - We are now asking for your and your child's consent for Part I of the study (the in-class questionnaire and the anthropometric measures). In February or March 2002, we will ask you separately and specifically for a consent for the blood sample. Both your school board and school principal fully support this project and have agreed that your child's class can participate. However your child's participation is completely voluntary, and it is entirely up to you and your child whether or not he/she participates. Your child can decide not to participate in the blood sample portion of the study and participate only in the questionnaires and anthropometric measures. Also, your child can withdraw from the study at any time and/or ask that his/her blood sample be destroyed before the end of the study by contacting the Project Coordinator (telephone number shown below). If you decide not to allow his/her participation, or if he/she withdraws from the study before it is completed, there will be no prejudice against your child.

Please complete the attached form to indicate whether or not your child will participate in Part I of the study, and return it to your child's teacher in the next 3 days. If you have any questions, please contact the Project Coordinator, Mrs. Elizabeth MacMillan-Davey at 528-2400 local 3976. We thank you and your child for your help in this important project.

[redacted]
Jennifer O'Loughlin, Ph.D.
Principal Investigator

[redacted]
Gilles Paradis, M.D.
Co-Investigator

*Santé physique*
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Hôpital général de Montréal
*mandataire*

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RÉGIE RÉGIONALE
DE LA SANTÉ ET DES
SERVICES SOCIAUX
**DE MONTRÉAL-CENTRE**

## MCGILL UNIVERSITY STUDY ON NICOTINE DEPENDENCE IN TEENS

Investigators: J. O'Loughlin, PhD., G. Paradis, MD, P. Clarke, PhD., J. Hanley, PhD, R. Tyndale, PhD., J. DiFranza, MD

### CONSENT FORM - PART I

(In-class questionnaire and anthropometric measures)

**Please complete and return this form to your child's teacher within 3 days.**

**Child's name:**

First name (please print clearly) _____ Last name (please print clearly) _____

☐ **Yes,** my child will participate in Part I of this study (i.e. the classroom questionnaire and the measurement of height, weight, skinfold thickness, waist circumference and blood pressure).

☐ **No,** my child will not participate in this study.

**PLEASE NOTE**: You are <u>not</u> consenting to the blood sample at this time. You will receive a separate consent form to sign for Part II (blood sample) in February or March 2002, just before the blood sample will be taken.

**Signatures**

| | | |
|---|---|---|
| Parent's name (please print) | Parent's signature | Date |
| Child's name (please print) | Child's signature | Date |

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DE MONTRÉAL-CENTRE

## APPROBATION DU PROJET PAR LE COMITÉ D'ÉTHIQUE

Le Comité d'éthique de santé publique de la Régie régionale de Montréal-Centre a examiné le projet de recherche :

**A prospective study on the natural history of nicotine dependence**

Soumis par: *Madame Jennifer O'Loughlin*

Le comité d'éthique a conclu que la recherche proposée respecte les règles éthiques en santé publique définies par la Régie régionale de Montréal-Centre.

***Membres du comité:***

| | |
|---|---|
| *M. Denis Allard* | *Agent de recherche* |
| *Dr. Robert Allard* | *Médecin* |
| *Mme Lorraine Bernier* | *Agente de recherche sociosanitaire* |
| *Dr. Nicole-Hébert-Croteau* | *Médecin-conseil* |
| *M. Alain Gauthier* | *Secrétaire général, C.S. Marguerite Bourgeois* |
| *Mme Marie Hirtle* | *Avocate* |
| *Mme Marcelle Monette* | *Conseillère à la recherche et au développement professionnel* |
| *Mme Francine Tardif* | *Sociologue consultante* |
| *M. Claudio Zanchettin* | *Professeur en philosophie* |
| *Dr. Bernard Heneman* | *Médecin-conseil et président du comité* |

[redacted]

*Président du comité*

99-04-07

*Date*

*Note:* Le présent certificat n'est valide que si une preuve d'acceptation du protocole pour son évaluation scientifique a été déposée auprès du comité d'éthique de la santé publique.

certifica.eth

# Appendix D: Guide to Time-Use Compositional Data Analysis (CoDA)

This guide is a brief walk through to the process of CoDA and its basic concepts in the context of time-use data. The aim of the guide is to introduce some CoDA concepts in a simple way that can orient researchers that plan to use CoDA with time-use data. It is important to note that this guide is by no means a reference, and researchers that aim to deepen their knowledge about CoDA should refer to the original sources and references included in this guide.

### Base Concepts in CoDA

Compositional Data analysis (CoDA) is an analytical method utilised to examine data when the data variables represent parts of a whole (Pawlowsky-Glahn & Buccianti, 2011). The whole is called a *composition* and is composed of a number of *d* parts. These parts are expressed as vectors of proportions or ratios of the whole. The sum of the parts always adds up to a constant value and the sum of the proportions adds up to 1 (100%). As a result of having a constant sum, compositional data lie within a constrained space called *Simplex*. The simplex is closed by the sum of the *d* parts, and data values inside the simplex are finite and can not exceed the closure sum (Aitchison, 1982; Pawlowsky-Glahn & Buccianti, 2011).

### CoDA in Context of Daily Time-use in Movement Behaviours

Time-use is compositional in nature as the daily time spent in any activity always belongs to either physical activity, sedentary behaviours or sleep. The sum of daily time spent in PA, SB and sleep always adds up to 24-hour and the sum of their proportions or percentages adds up to 1 (100%). This can be shown as follows (Chastin & Palarea-Albaladejo, 2015):

$$t_{\text{24-hour}} = t_{\text{MVPA}} + t_{\text{walking}} + t_{\text{SB}} + t_{\text{sleep}}$$

and the compositional form can similarly be expressed as :

$$(100\%)\, t_{\text{24-hour}} = (\%)\, t_{\text{MVPA}} + (\%)\, t_{\text{walking}} + (\%)\, t_{\text{SB}} + (\%)\, t_{\text{sleep}}$$

**Normalisation Process**

After the collection of daily time spent in different movement behaviours in any given dataset, CoDA is conducted by converting the absolute amounts of time spent in movement behaviours, for each participant in the dataset, to proportions or ratios of their sum. This can easily be achieved using the acomp() function in R package "compositions" (Boogaart, Tolosana-Delgado, & Bren, 2020). This function closes movement behaviours values for each participant in the dataset to ratios of their sum wherein the sum of ratios of behaviours for each participants is constant and equals to 1 (Chastin & Palarea-Albaladejo, 2015).

**Treating Zero Values in a Compositional Dataset:**

CoDA relies heavily on log-ratios, thus zero values in any compositional dataset should be treated before conducting analysis. Zero values in the dataset can be rounded or absolute zeros. There are different techniques to deal with each type of zero values, however deciding the type of zero values and the ideal method of treatment depends on the dataset and its measurement methods. We leave the decision to the researchers who conduct the analysis and refer them to the work of Pawlowsky-Glahn et al. for more details on the subject (Pawlowsky-Glahn & Buccianti, 2011). We recommend using R package "zCompositions" to apply the selected zero replacement method (Palarea-Albaladejo, Martín-Fernández, & Systems, 2015).

**Descriptive Statistics of Compositional Data Inside the Simplex Space:**

Due to the constrained nature of the simplex space that contains compositional data, regular descriptive statistics do not apply to compositional data (Chastin & Palarea-Albaladejo, 2015). Instead, central tendency of the data inside the simplex is best described by the compositional geometric mean. Compositional geometric mean is estimated by calculating the geometric mean of each behaviour in the compositional dataset, then the geometric means of all behaviours are scaled to the same scale used to close the compositional data. For instance if behaviours in the dataset are closed to ratios from the sum that add up to 1, then all geometric means are scaled to ratios of their sum that add up to 1 representing the compositional geometric mean of the dataset (Chastin & Palarea-Albaladejo, 2015).

Geometric mean (g) is calculated using the formula:

$$g = \sqrt[n]{(X_1 \times X_2 \times ... \times X_n)}$$

where $X_i$ is a behaviour in a compositional dataset and n is the number of occurrences of this behaviour which equals the number of participants.

and the compositional geometric mean can be expressed as (Chastin & Palarea-Albaladejo, 2015):

$$cen = C(g_1, g_2, ..., g_d)$$

where C is the closure operator of the compositional dataset and d is the number of parts or behaviours in the dataset.

The compositional geometric mean can be calculated using the function mean() of a compositional dataset once its class is defined as "acomp" which means Aitchison composition (Aitchison, 1982).

Similarly, the variance of the data in the simplex space is best described by a variation matrix. Variation matrix is a symmetrical matrix that describes the co-dependence between parts inside the simplex space by estimating the variances in logarithms of all pairwise ratios of all parts (Chastin & Palarea-Albaladejo, 2015; Pawlowsky-Glahn & Buccianti, 2011). The variation matrix can be simply calculated using the function variation () of the package "compositions" (Boogaart et al., 2020).

**Transformation of compositional data to real space:**

Since compositional data is constrained in the simplex space, the data can not be used with standard statistical tests such as regression which only applies to data in real space that can vary freely between [-∞, ∞] (Chastin & Palarea-Albaladejo, 2015; Pearson, 1897) . As such, compositional data must be transformed to equivalent values in real space. Multiple methods of transformation exist, but isometric log-ratio transformation is the preferred method of transformation with time-use data. For a compositional set of d parts, each part or behaviour is transformed to real space by a set of d-1 ilr coordinates. Thus, in a set similar to ours with 4 parts (MVPA, walking, SB, sleep), we obtain a set of 3 ilr coordinates for each behaviour with

a total of 4 sets of ilr coordinates. In our 4 parts dataset as an example, 3 ilr coordinates for MVPA, for example, are calculated as follows (Chastin & Palarea-Albaladejo, 2015):

$$Z1 = \sqrt{\frac{3}{4}} In \frac{MVPA}{\sqrt[3]{walking + SB + sleep}}$$

$$Z2 = \sqrt{\frac{2}{3}} In \frac{walking}{\sqrt[2]{SB + sleep}}$$

$$Z3 = \sqrt{\frac{1}{2}} In \frac{SB}{\sqrt{sleep}}$$

Where Z1, Z2, Z3 are the 3 ilr coordinates for MVPA. Ilr coordinates can be calculated using ilr() function in R package "compositions" (Boogaart et al., 2020).

**Log-ratio multiple regression model**

Once each movement behaviour in the compositional dataset is transformed from simplex space into equivalent ilr coordinates in real space, the ilr coordinates can be fitted in a standard regular multiple regression model. it is important to note that in a compositional dataset with 4 behaviours (d = 4), there are 4 different sets of ilr coordinates with one set for each behaviour. Each set of ilr coordinates has to be fitted separately in a multiple regression model with a total of 4 multiple regression models. Ilr multiple regression models the following formula (Chastin & Palarea-Albaladejo, 2015; Pawlowsky-Glahn & Buccianti, 2011):

$$Y_i = \beta_0 + \beta^b\, ilr(x_i) + \text{Cov}$$

Where $Y$ is the outcome of interest for participants i = (1, 2, …, n), $x$ is a specific movement behaviour for participants i, $\beta_0$ is the intercept of the model, $\beta^b$ is the coefficient of ilr coordinates of behaviour $x$ and Cov is the covariables included in the model. Since we have 3 ilr coordinates for each behaviour, the previous formula can be further expressed as (Chastin & Palarea-Albaladejo, 2015; Pawlowsky-Glahn & Buccianti, 2011):

$$Y_i = \beta_0 + \beta^b{}_1 Z_1 + \beta^b{}_2 Z_2 + \beta^b{}_3 Z_3 + \text{Cov}$$

Where $Z_1$, $Z_2$, $Z_3$ are the ilr coordinates of a behaviour in the compositional dataset. It is important to note that the 4 different fitted regression models, one for each set of ilr coordinates of each behaviour in the set, have the same intercept, coefficients of covariables, $R^2$ and p-values. The ilr regression model can be conducted in R using the base linear regression function lm().

Finally, we provide a checklist that we believe can facilitate the work of future researchers aiming to conduct CoDA analysis in context of Time-use epidemiology. In the checklist, we list items that we came across during our analysis as well as the decisions that were taken for each item. The listed decisions only work as a guideline for future research, but they are not be any means obligatory and we understand that different decisions can be taken for different studies using different variables and or measurement tools.

**A checklist for CoDA with time-use data and the decisions taken during analysis**

| Checklist Item | Decision taken during analysis |
|---|---|
| 1. Was the data collection conducted with the aim of measuring the maximum daily time spent in different movement behaviours? | Yes, however some light physical activity behaviours were not measured. |
| 2. Were participants with missing values excluded from analysis? | Yes. |
| 3. Were participants with aberrant movement behaviour values that exceed 24-hour daily excluded from analysis? | Yes. |
| 4. Were participants with discrepant movement behaviour values who reported number of minutes of behaviours but zero days doing that behaviour excluded from analysis? | Yes. |
| 5. Were PA bouts that exceeded 180 minutes daily truncated as per the IPAQ-SF questionnaire guidelines? | Yes, and there was no significant difference in averages of PA between those excluded from and included in analysis |
| 6. Did the study use daily time cut offs to determine the minimum number of hours daily needed of | No, we refrained from using minimum daily hours cut offs as there is no specific guideline to |

| | |
|---|---|
| movement behaviours for a participant to be included in analysis | use and we aimed to maximize number of participants retained for analysis |
| 7a. Was the dataset examined for presence of zero values? | Yes. |
| 7b. Was the type of zero values discussed and decided based on the measurement tool detection limit? | Yes, and we decided that zero values in our dataset are rounded zero as IPAQ-SF questionnaire has detection limit of 10 minutes of weekly PA bouts. |
| 7c. Were zero values treated based on their type before conducting CoDA? | Yes, zero values were treated using simple multiplicative replacement method since zero values in the dataset were less than 10% of total values. |
| 7d. Was a sensitivity analysis conducted to ensure that there was no data distortion after zero values replacement? | Yes, a sensitivity analysis using log-normal multiplicative replacement of zeros was conducted. |
| 8. Were data normalised and converted to its compositional form? | Yes. |
| 9. Were descriptive statistics of compositional data such as compositional geometric mean and variation matrix estimated? | Yes. |
| 10a. Were compositional data transformed to real space using the appropriate log-ratio transformation method? | Yes, we used an isometric log-ratio transformation technique. |
| 10b. Was a separate set or coordinates created for each behaviour in the compositional dataset? | Yes, we obtained a separate set of ilr coordinates for each of the 4 movement behaviours in our dataset. |
| 11. Were the obtained sets of coordinated fitted in its own separate regression model? | Yes, we fitted 4 different ilr multiple regression models, one for each set of ilr coordinates. |
| 12. Was p-value of the first ilr coordinate of each behaviour used to examine the significance of the association with the outcome variable? | Yes. |

**References**:


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Chastin, S., & Palarea-Albaladejo, J. (2015). SUPPLEMENTARY MATERIAL S2: CONCISE GUIDE TO COMPOSITIONAL DATA.

Chastin, S. F., Palarea-Albaladejo, J., Dontje, M. L., & Skelton, D. A. J. P. o. (2015). Combined effects of time spent in physical activity, sedentary behaviors and sleep on obesity and cardio-metabolic health markers: a novel compositional data analysis approach. *10*(10), e0139984.

Palarea-Albaladejo, J., Martín-Fernández, J. A., & Systems, C. I. L. (2015). zCompositions—R package for multivariate imputation of left-censored data under a compositional approach. *143*, 85-96.

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Pearson, K. (1897). Mathematical contributions to the theory of evolution.—on a form of spurious correlation which may arise when indices are used in the measurement of organs. *Proceedings of the royal society of london, 60*(359-367), 489-498.

# Appendix E: Example of R Code Used in Analysis

Adding R packages of compositional analysis

```
install.packages("compositions")
library(compositions)
```

Dealing with zeros in my dataset

```
# creating a matrix with variables and converting it to a compositional obj
ect

MB = compos.analytical_sample %>% dplyr::select(sleep21, SB21_mins, LPA21,
MVPA21)
MB = acomp(MB)

# installing and loading zcompositions package
install.packages("zCompositions")
library(zCompositions)

# detection limit of VPA, MPA or LPA = 10 minutes per week. So, we divide 1
0 minutes by 7 days = average 1.428571 minutes daily. this number of minute
s is changed to proportion of the day by dividing by 1440 so 1.428571/1440
= 0.000992
# creating a detection limit values for imputation
dldif = c(0,0,0.000992,0.000992) # we added dls only for LPA and MVPA, sinc
e we have no zeros in sleep or SB


# using multrep1 () function to impute zeros, (delta is identified as 0.65
of the detection limit)
MB.multrep1 = multRepl(MB, label = 0, dl = dldif, delta = 0.65)

 #converting the imputed set to an Aitchison composition
MB.multrep = acomp(MB.multrep1)
```

Calculating the compositional geometric mean and variation matrices

```
comp.mean = mean(MB.norm.comp) # note that the sum of means is 100% and aco
mp means Aitchison composition


var.matrix = variation(MB.norm.comp)

#calculation using the formula of exp(-t^2/2) to get co-dependence of propo
rtions (Chastin 2015), rounded to 8 digits for readability
round(exp(-(var.matrix)^2/2), digits = 8)
```

Creating other models using the other sets of ilr coordinates (requires creating compositions with different parts order)

```
sleep.ilr = MB.multrep1 %>% select(SB21_mins, LPA21, MVPA21, sleep21)
sleep.ilr = acomp(sleep.ilr)
lm(MDI22~ilr(sleep.ilr)+AGEIY_21+factor(Sex)+factor(Edu21_adj)+MDI21, data
= compos.analytical_sample) %>% summary()
lm(MDI22~ilr(sleep.ilr)+AGEIY_21+factor(Sex)+factor(Edu21_adj)+MDI21, data
= compos.analytical_sample) %>% confint()

SB.ilr = MB.multrep1 %>% select(sleep21, LPA21, MVPA21, SB21_mins)
SB.ilr = acomp(SB.ilr)
lm(MDI22~ilr(SB.ilr)+AGEIY_21+factor(Sex)+factor(Edu21_adj)+MDI21, data = c
ompos.analytical_sample) %>% summary()
lm(MDI22~ilr(SB.ilr)+AGEIY_21+factor(Sex)+factor(Edu21_adj)+MDI21, data = c
ompos.analytical_sample) %>% confint()

walking.ilr = MB.multrep1 %>% select(sleep21, SB21_mins,MVPA21, LPA21)
walking.ilr = acomp(walking.ilr)
lm(MDI22~ilr(walking.ilr)+AGEIY_21+factor(Sex)+factor(Edu21_adj)+MDI21, dat
a = compos.analytical_sample) %>% summary()
lm(MDI22~ilr(walking.ilr)+AGEIY_21+factor(Sex)+factor(Edu21_adj)+MDI21, dat
a = compos.analytical_sample) %>% confint()

MVPA.ilr = MB.multrep1 %>% select(sleep21, SB21_mins, LPA21, MVPA21)
MVPA.ilr = acomp(MVPA.ilr)
lm(MDI22~ilr(MVPA.ilr)+AGEIY_21+factor(Sex)+factor(Edu21_adj)+MDI21, data =
compos.analytical_sample) %>% summary()
lm(MDI22~ilr(MVPA.ilr)+AGEIY_21+factor(Sex)+factor(Edu21_adj)+MDI21, data =
compos.analytical_sample) %>% confint()
```

The prediction of MDI score at the compositional mean (covariables will remain constant across all predictions)

```
# estimating the compositional mean
comp.mean = mean(MB.norm.comp)
#prediction around the compositional mean
mean.pred = predict(lm, newdata = list(MB.norm.comp = comp.mean, AGEIY_21=
mean(compos.analytical_sample$AGEIY_21), Sex= 1, Edu21_adj = 1, MDI21 = mea
n(compos.analytical_sample$MDI21)))
```

Example of isotemporal reallocation of time model using 15 minutes of reallocation between behaviours keep in mind it doesn't matter what values we use with the covariables, as these values will remain constant and the only change will be in the values around the mean. thus, upon calculating the difference in prediction the constant values will be equal on both sides of the equation. 1-from SB to other behaviours

```
# creating a matrix with the compositional mean
comp.mean.matrix <- matrix(comp.mean, ncol=4, byrow=TRUE)
```

```
# reallocating 15/1440 from SB to MVPA
new.comp1 <- acomp(comp.mean.matrix + c (0, -15/1440, 0, 15/1440))


# prediction of MDI score values after reallocation
pred1 = predict(lm, newdata = list(MB.norm.comp= new.comp1, AGEIY_21= mean(
compos.analytical_sample$AGEIY_21), Sex= 1 , Edu21_adj = 1 , MDI21= mean(co
mpos.analytical_sample$MDI21)))

# prediction difference 1
pred1 - mean.pred

# reallocating 15 mins from SB to LPA
new.comp2 <- acomp(comp.mean.matrix + c (0, -15/1440, 15/1440, 0))

pred2 = predict(lm, newdata = list(MB.norm.comp= new.comp2, AGEIY_21= mean(
compos.analytical_sample$AGEIY_21), Sex= 1 , Edu21_adj = 1  , MDI21= mean(c
ompos.analytical_sample$MDI21)))

# prediction difference 2
pred2 - mean.pred

#reallocating 15 mins from sb to sleep
new.comp3 <- acomp(comp.mean.matrix + c (15/1440, -15/1440, 0, 0))

pred3 = predict(lm, newdata = list(MB.norm.comp= new.comp3, AGEIY_21= mean(
compos.analytical_sample$AGEIY_21), Sex= 1 , Edu21_adj = 1, MDI21= mean(com
pos.analytical_sample$MDI21)))

# prediction difference 3
pred3 - mean.pred
```

2-From sleep to other behaviours

```
# creating a matrix with the compositional mean
comp.mean.matrix <- matrix(comp.mean, ncol=4, byrow=TRUE)


# reallocating 15/1440 from sleep to MVPA
new.comp1 <- acomp(comp.mean.matrix + c (-15/1440, 0, 0, 15/1440))

# prediction of MDI score values after reallocation
pred1 = predict(lm, newdata = list(MB.norm.comp= new.comp1, AGEIY_21= mean(
compos.analytical_sample$AGEIY_21), Sex= 1 , Edu21_adj = 1 , MDI21= mean(co
mpos.analytical_sample$MDI21)))

# prediction difference 1
```

```
pred1 - mean.pred

# reallocating 15 mins from sleep to LPA
new.comp2 <- acomp(comp.mean.matrix + c (-15/1440, 0, 15/1440, 0))

pred2 = predict(lm, newdata = list(MB.norm.comp= new.comp2, AGEIY_21= mean(
compos.analytical_sample$AGEIY_21), Sex= 1 , Edu21_adj = 1  , MDI21= mean(c
ompos.analytical_sample$MDI21)))

# prediction difference 2
pred2 - mean.pred

#reallocating 15 mins from sleep to SB
new.comp3 <- acomp(comp.mean.matrix + c (-15/1440, 15/1440, 0, 0))

pred3 = predict(lm, newdata = list(MB.norm.comp= new.comp3, AGEIY_21= mean(
compos.analytical_sample$AGEIY_21), Sex= 1 , Edu21_adj = 1, MDI21= mean(com
pos.analytical_sample$MDI21)))

# prediction difference 3
pred3 - mean.pred
```

3-from walking to other behaviuors

```
# creating a matrix with the compositional mean
comp.mean.matrix <- matrix(comp.mean, ncol=4, byrow=TRUE)

# reallocating 15/1440 from LPA to MVPA
new.comp1 <- acomp(comp.mean.matrix + c (0, 0, -15/1440, 15/1440))

# prediction of MDI score values after reallocation
pred1 = predict(lm, newdata = list(MB.norm.comp= new.comp1, AGEIY_21= mean(
compos.analytical_sample$AGEIY_21), Sex= 1 , Edu21_adj = 1 , MDI21= mean(co
mpos.analytical_sample$MDI21)))

# prediction difference 1
pred1 - mean.pred

# reallocating 15 mins from LPA to sleep
new.comp2 <- acomp(comp.mean.matrix + c (15/1440, 0, -15/1440, 0))

pred2 = predict(lm, newdata = list(MB.norm.comp= new.comp2, AGEIY_21= mean(
compos.analytical_sample$AGEIY_21), Sex= 1 , Edu21_adj = 1  , MDI21= mean(c
ompos.analytical_sample$MDI21)))

# prediction difference 2
pred2 - mean.pred

#reallocating 15 mins from LPA to SB
```

```
new.comp3 <- acomp(comp.mean.matrix + c (0, 15/1440, -15/1440, 0))

pred3 = predict(lm, newdata = list(MB.norm.comp= new.comp3, AGEIY_21= mean(
compos.analytical_sample$AGEIY_21), Sex= 1 , Edu21_adj = 1, MDI21= mean(com
pos.analytical_sample$MDI21)))

# prediction difference 3
pred3 - mean.pred
```

4-from MVPA to other behaviours

```
# creating a matrix with the compositional mean
comp.mean.matrix <- matrix(comp.mean, ncol=4, byrow=TRUE)

# reallocating 15/1440 from MVPA to LPA
new.comp1 <- acomp(comp.mean.matrix + c (0, 0, 15/1440, -15/1440))

# prediction of MDI score values after reallocation
pred1 = predict(lm, newdata = list(MB.norm.comp= new.comp1, AGEIY_21= mean(
compos.analytical_sample$AGEIY_21), Sex= 1 , Edu21_adj = 1 , MDI21= mean(co
mpos.analytical_sample$MDI21)))

# prediction difference 1
pred1 - mean.pred

# reallocating 15 mins from MVPA to sleep
new.comp2 <- acomp(comp.mean.matrix + c (15/1440, 0, 0, -15/1440))

pred2 = predict(lm, newdata = list(MB.norm.comp= new.comp2, AGEIY_21= mean(
compos.analytical_sample$AGEIY_21), Sex= 1 , Edu21_adj = 1  , MDI21= mean(c
ompos.analytical_sample$MDI21)))

# prediction difference 2
pred2 - mean.pred

#reallocating 15 mins from MVPA to SB
new.comp3 <- acomp(comp.mean.matrix + c (0, 15/1440, 0, -15/1440))

pred3 = predict(lm, newdata = list(MB.norm.comp= new.comp3, AGEIY_21= mean(
compos.analytical_sample$AGEIY_21), Sex= 1 , Edu21_adj = 1, MDI21= mean(com
pos.analytical_sample$MDI21)))

# prediction difference 3
pred3 - mean.pred
```

# Appendix F: Supplementary Material

Supplementary Table 1. range of values for characteristics of participants retained and not retained for analysis (n=1294), NDIT, 1999-2012

| Range of Values of | Retained (n = 729) | Not Retained (n = 565) |
|---|---|---|
| Age, y. | | |
| Cycle 21 | 18.4 - 23.6 | 18.7 - 24.4 |
| Cycle 22 | 22.2 - 26.8 | 22.6 - 27.8 |
| Depressive Symptoms | | |
| Cycle 21 | 0 - 50 | 0 - 36 |
| Cycle 22 | 0 - 49 | 0 - 37 |
| MVPA (min/day) | 0 - 360 | 0 – 308.6 |
| Walking (min/day) | 0 - 180 | 0 - 180 |
| Sedentary Behaviour (min/day) | 30 - 1560 | 30 - 2777.1 |
| Sleep (min/day) | 210 - 840 | 285 - 1380 |

MVPA = Moderate to Vigorous Physical Activity

Supplementary Table 2. Compositional variation matrix of co-dependence between time spent in sleep, sedentary behavior, walking and moderate to vigorous physical activity inside the simplex space (n = 729), NDIT 1999-2012

| | MVPA | Walking | SB | Sleep |
|---|---|---|---|---|
| MVPA | 0.000 | 5.713 | 4.355 | 4.056 |
| Walking | 5.713 | 0.000 | 2.720 | 2.359 |
| SB | 4.355 | 2.720 | 0.000 | 0.397 |
| Sleep | 4.056 | 2.359 | 0.397 | 0.000 |

MVPA = Moderate to Vigorous Physical Activity, SB = Sedentary Behaviour
Values closer to zero indicate high co-dependence between the proportion of time spent in each pair of behaviours

Supplementary Table 3. Change in prediction matrices showing the difference in predicted depressive symptoms values with reallocation of 10, 15, 20, 25 and 30 minutes from the behaviours in columns to the behaviours in rows (n = 729), NDIT 1999-2012.

| Reallocation of 10 Minutes | | | | | Reallocation of 15 Minutes | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | MVPA | Walking | SB | Sleep | | MVPA | Walking | SB | Sleep |
| MVPA | - | 0.130 | 0.122 | 0.119 | MVPA | - | 0.280 | 0.269 | 0.265 |
| Walking | -0.080 | - | -0.013 | -0.016 | Walking | -0.117 | - | -0.024 | -0.029 |
| SB | -0.067 | 0.008 | - | -0.003 | SB | -0.093 | 0.010 | - | -0.004 |
| Sleep | -0.065 | 0.010 | 0.003 | - | Sleep | -0.089 | 0.015 | 0.004 | - |
| | | | | | | | | | |
| Reallocation of 20 Minutes | | | | | Reallocation of 25 Minutes | | | | |
| | MVPA | Walking | SB | Sleep | | MVPA | Walking | SB | Sleep |
| MVPA | - | -* | -* | -* | MVPA | - | -* | -* | -* |
| Walking | -0.160 | - | -0.046 | -0.051 | Walking | -* | - | -* | -* |
| SB | -0.115 | 0.013 | - | -0.006 | SB | -0.134 | 0.014 | - | -0.007 |
| Sleep | -0.109 | 0.018 | 0.006 | - | Sleep | -0.127 | 0.021 | 0.007 | - |
| | | | | | | | | | |

| Reallocation of 30 Minutes | | | | |
|---|---|---|---|---|
| | MVPA | Walking | SB | Sleep |
| MVPA | - | -* | -* | -* |
| Walking | -* | - | -* | -* |
| SB | -0.152 | 0.016 | - | -0.009 |
| Sleep | -0.143 | 0.025 | 0.008 | - |

MVPA = Moderate to Vigorous Physical Activity, SB = Sedentary Behaviours

Negative values indicate reduction in depressive symptoms predicted values with time reallocation, while positive values indicate an increase in predicted values with time reallocation

*reallocation is not applicable as behaviour value at the compositional mean is less than the reallocation time.

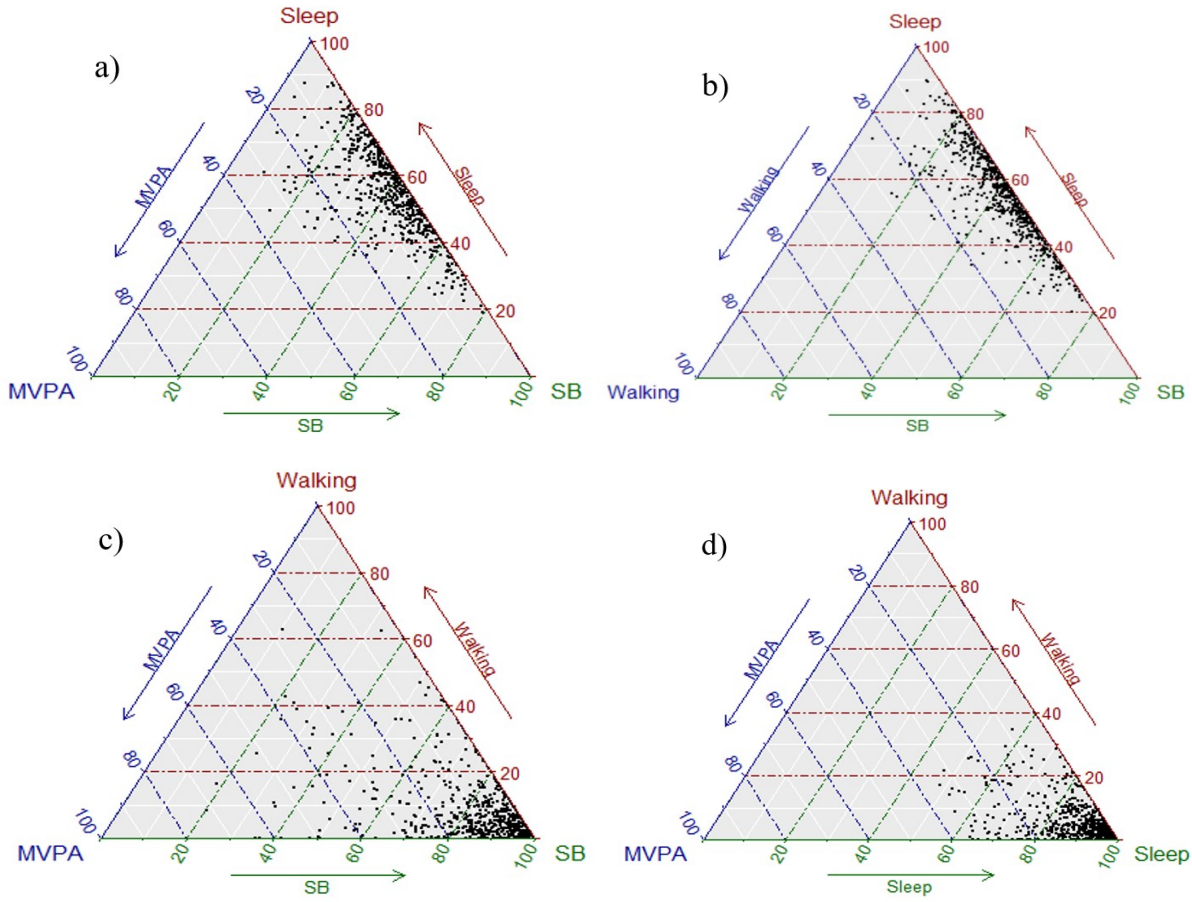
Supplementary Table 4. Comparison of characteristics of participants retained and not retained for analysis from cycle 21 (n = 880), NDIT 1999–2012

| | Retained (n = 729) | Not retained (n = 151) |
|---|---|---|
| Age, y. mean (SD) | | |
| Cycle 21 | 20.3 (0.7) | 20.7 (0.9) |
| Cycle 22 | 24.0 (0.7) | 24.2 (0.9) |
| Female, % | 56.0 | 45.0 |
| Language other than French, % | 69.4 | 67.5 |
| Born in Canada, % | 93.6 | 92.7 |
| Mother university-educated, % | 42.9 | 24.5 |
| Highest education level attained*, % | | |
| High school | 20.6 | 41.1 |
| CEGEP/Technical school | 59.9 | 47.0 |
| University | 19.5 | 11.3 |
| Depressive symptoms, mean (SD) | | |
| Cycle 21 | 9.7 (7.8) | 9.75 (7.6) |
| Cycle 22 | 8.4 (7.8) | 7.59 (8.0) |
| MVPA (min/day), mean (SD) | 39.0 (54.3) | 43.0 (61.2) |
| Walking (min/day), mean (SD) | 33.3 (41.8) | 32.0 (42.2) |
| Sedentary behavior (min/day), mean (SD) | 413.6 (242.8) | 510 (422) |
| Sleep (min/day), mean (SD) | 501.1 (87.5) | 500 (135) |

CEGEP = Collège d'enseignement général et professionnel, MVPA = Moderate-to-Vigorous intensity Physical Activity; SB = Sedentary Behaviours; SD = Standard Deviation

* Highest education level attained is reported in NDIT cycle 21

Supplementary Figure 1. Ternary plots of the proportion of sleep, sedentary behaviour (SB), walking and moderate to vigorous PA (MVPA) inside the simplex space (n = 729), NDIT 1999-2012




The distribution of movement behaviours inside the simplex space is shown using multiple Ternary plots (Supplementary Figure 1), each representing three behaviours. We did not plot all four behaviours because this requires a 3-dimentional plot, which is difficult to interpret (Chastin, Palarea-Albaladejo, Dontje, & Skelton, 2015). In the ternary plots, each vertex represents a behaviour, and each point represents the relative proportion of the three behaviours in the plot. The closer the point to a vertex, the higher the proportion of the behaviour in the vertex in relation to other behaviours. In plots "a" and "b" (Supplementary Figure 1), most values are far from MVPA and walking, indicating their low proportions inside the simplex space. In plots "c" and "d", most values are closer to sleep and SB, indicating the high representation of their proportions inside the simplex space.

# Appendix G : Variables Distribution Histograms

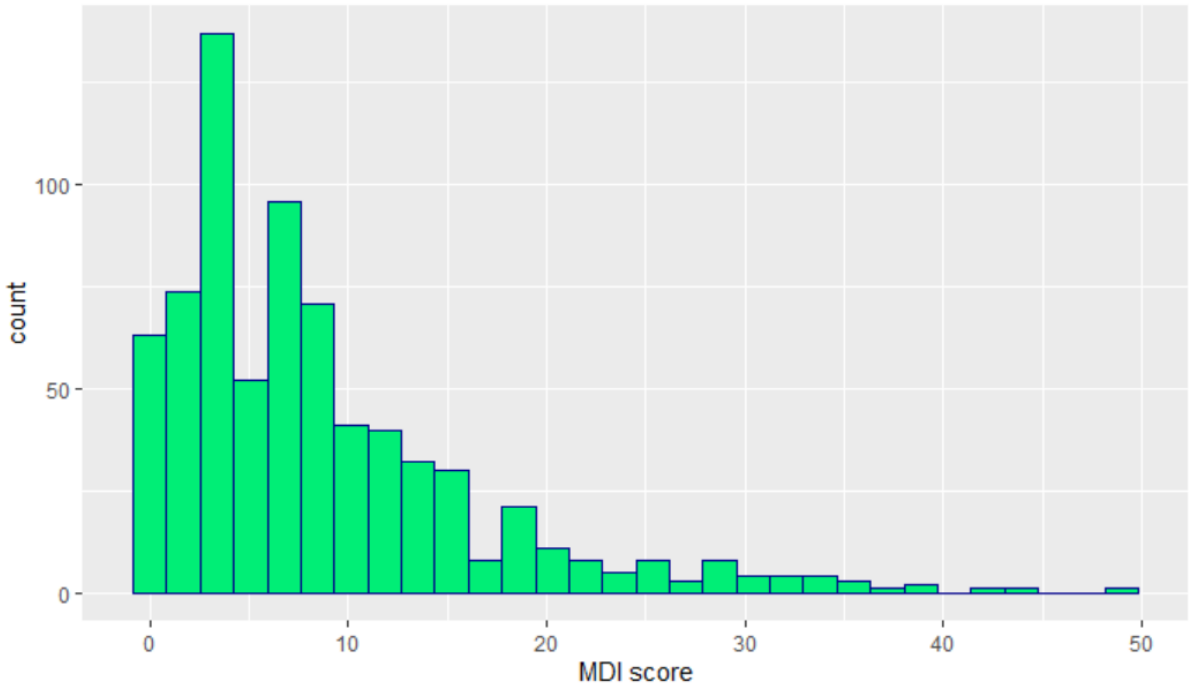



Figure 16. Histogram for the distribution of Depressive symptoms MDI score in cycle 22 (n = 729), NDIT 1999-2012.

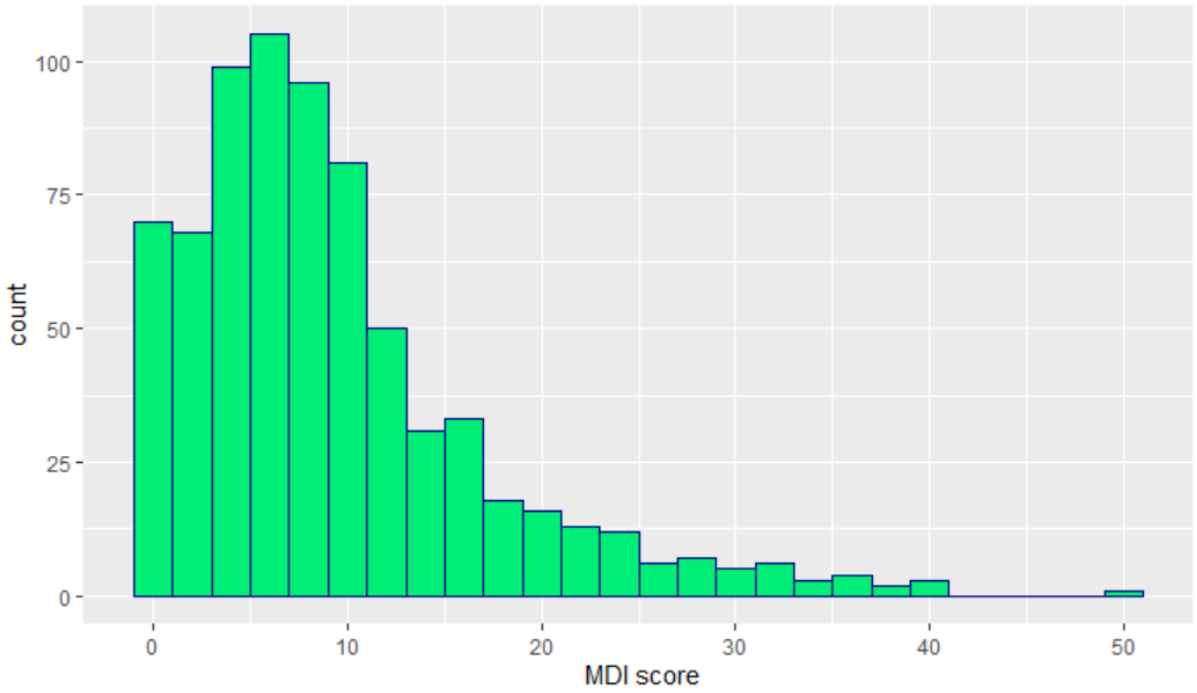



Figure 17. Histogram for the distribution of depressive symptoms MDI score in cycle 21 (n = 729), NDIT 1999-2012.

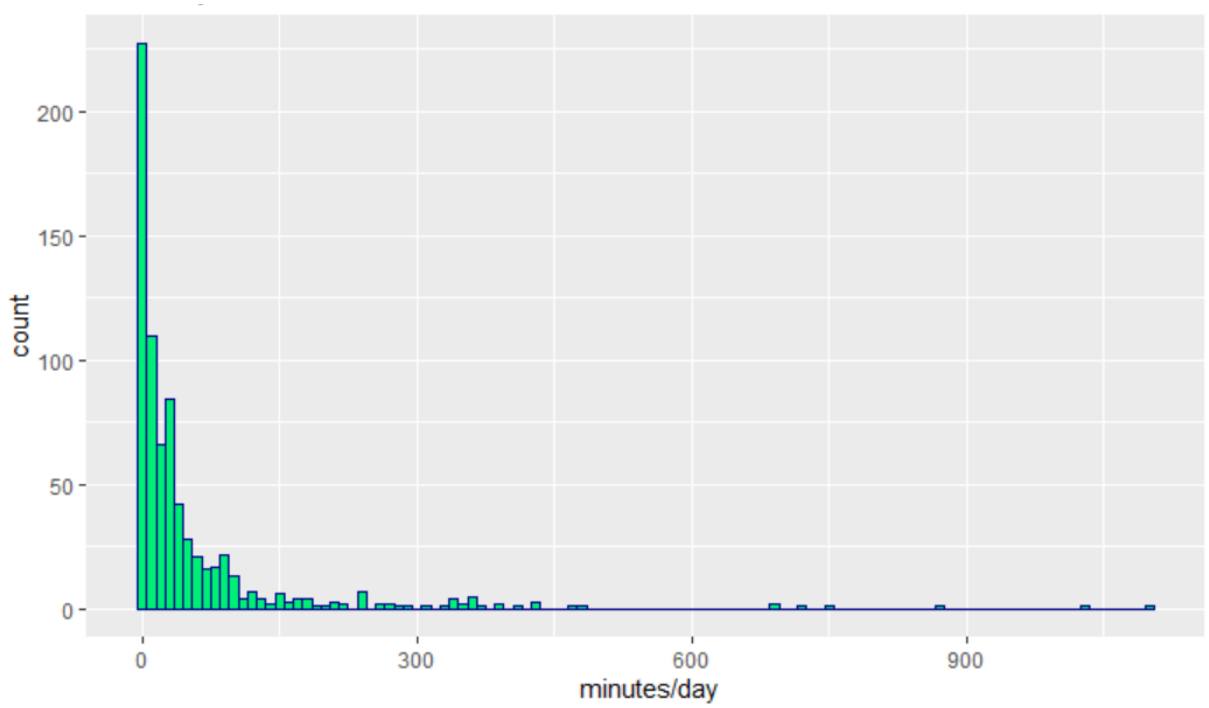



Figure 18. Histogram for the distribution of time spent in Moderate-to-vigorous intensity physical activity (MVPA) daily in minutes in cycle 21 (n = 729), NDIT 1999-2012.

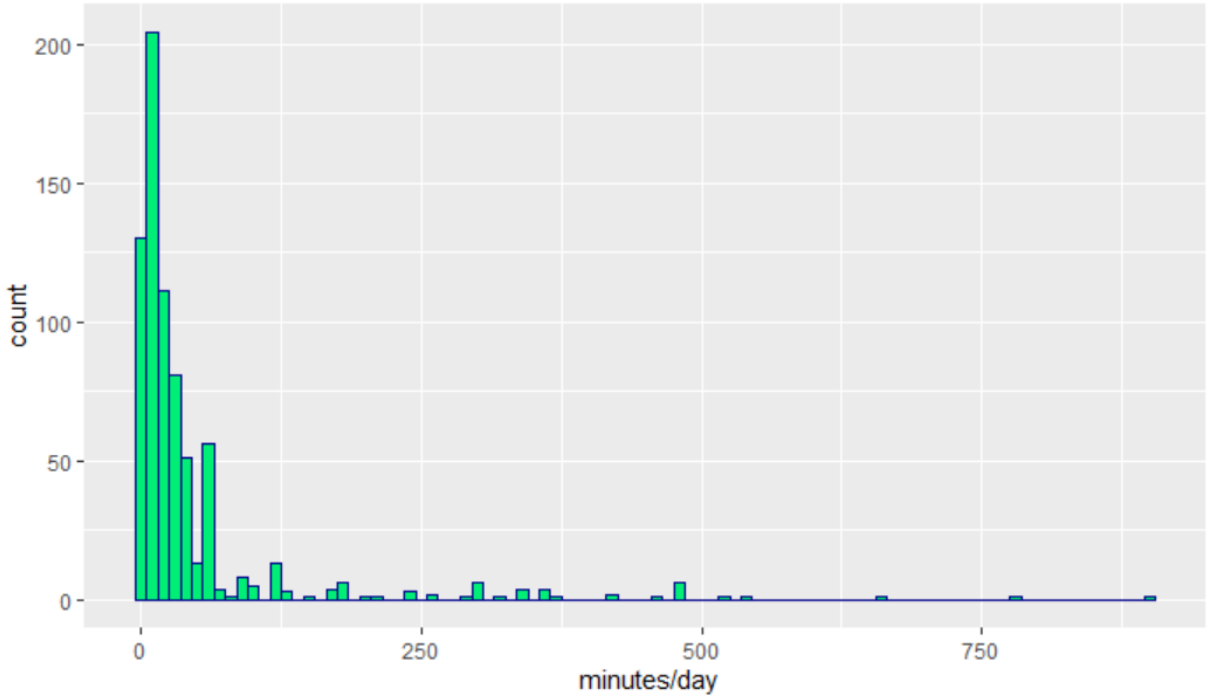



Figure 19. Histogram for the distribution of time spent walking daily in minutes in cycle 21 (n = 729), NDIT 1999-2012.

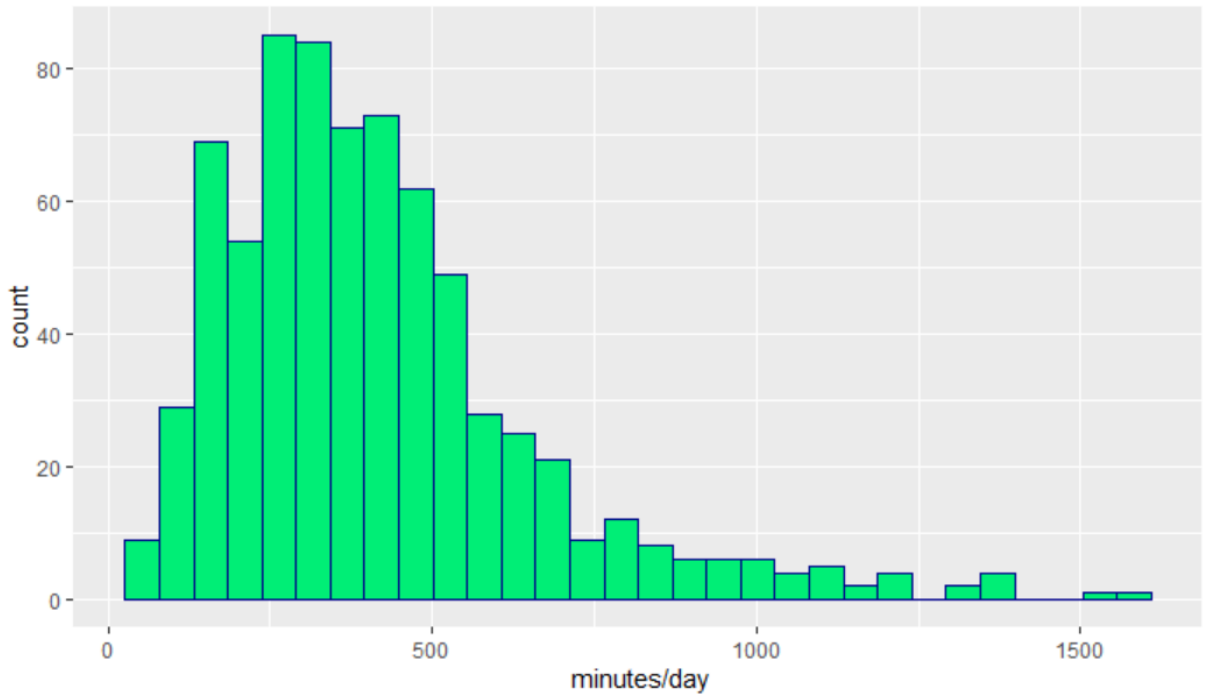



Figure 20. Histogram for the distribution of time spent in sedentary behaviours daily in minutes in cycle 21 (n = 729), NDIT 1999-2012.

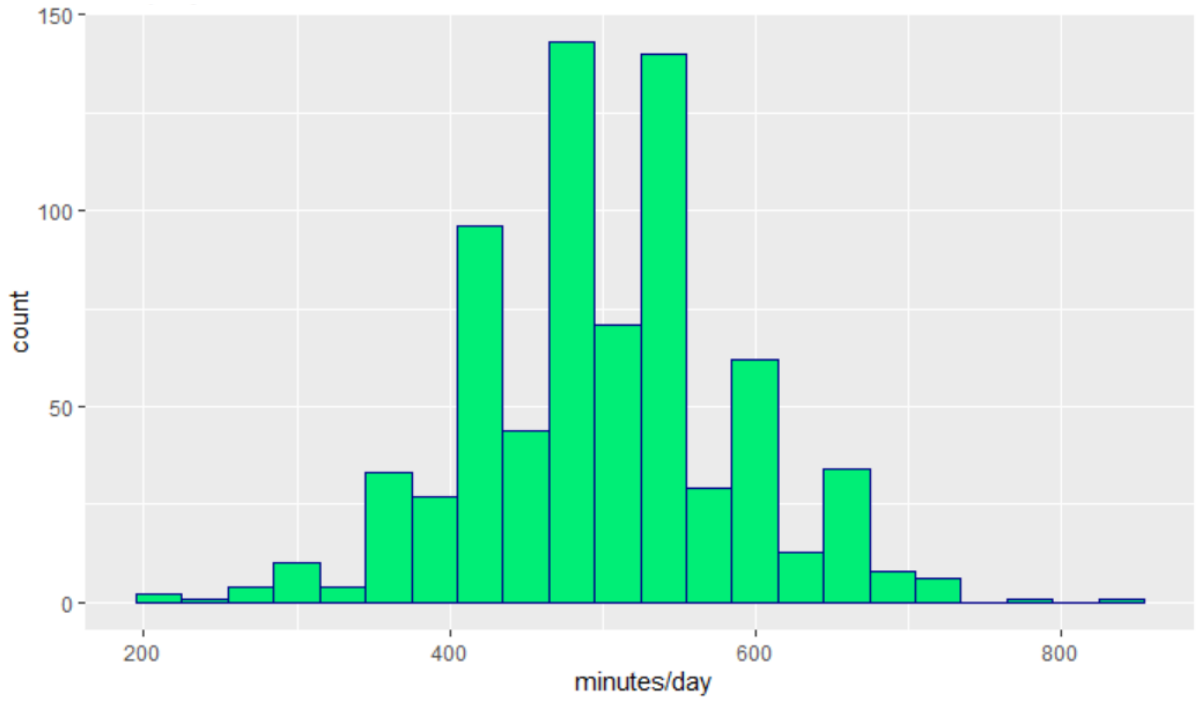



Figure 21. Histogram for the distribution of time spent sleeping daily in minutes in cycle 21 (n = 729), NDIT 1999-2012.